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Putting a Price on Safety

A Hedonic Price Approach to Flood Risk in African Cities

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Abstract

This paper uses a hedonic property price function to estimate the relationship between flood risk and rents in four Sub-Saharan Africa cities: Accra, Antananarivo, Dar es Salaam, and Addis Ababa. The analysis relies on household survey data collected after flood events in the cities. Flood risk is measured with self-reported data on past flood exposure and perception of future risk of flooding of households. The study finds that flood risk is associated with lower rents in Accra, Antananarivo, and Addis Ababa, ranging from 14 to 56 percent lower. In contrast, risk is associated with higher rent in Dar es Salaam, which could be potentially attributed to a combination of lack of awareness of flood risk among renters, high transaction costs and omitted variable bias. For example, only 12 percent of households living in flood-prone areas were aware of the flood risk when they moved in. In Antananarivo, job density is associated with higher rents while in Accra and Addis Ababa, higher job density is associated with lower rents. Results are negative but not significant in Dar es Salaam. When interacting job density with flood risk for each city, the negative effect of job density on rents is higher (in absolute value) when flood risk is high in Accra and Addis Ababa, and the positive effect of job density on rents becomes negative when flood risk is high in Antananarivo. This relationship is not found in Dar es Salaam. The finding seems to suggest that access to jobs is a factor driving people to settle in flood-prone areas.

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Putting a Price on Safety – a Hedonic Price Approach to Flood Risk in African Cities[*]

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1 Introduction

Urban risks related to climate change are increasing (IPCC, 2014). Over half of cities with more than 500,000 inhabitants are at high risk of exposure to at least one type of natural disaster. Countries in Sub-Saharan Africa (SSA) have experienced high rates of urbanization in recent decades, and it is expected that between 2018 and 2050 the SSA urban population will triple (UN, 2019). Unfortunately, the journey to urbanization in SSA has been accompanied by increasing numbers of informal settlements, poor quality public services and infrastructure (Castells-Quintana and Wenban-Smith, 2020; Fay and Opal, 1999), and little or no preparedness for natural disasters. These conditions make SSA urban populations extremely vulnerable to natural disasters and especially floods, which are frequent and often very severe. In the absence of insurance markets and other risk transfer options, much of the impact of flooding is absorbed by the households, resulting in enormous costs, which accumulate over time and pose a threat to development gains (Erman et al., 2020). In a context of climate change, increasing urbanization and a predicted "lost decade" of development due to the COVID-19 crisis (WB, 2021), it is important to understand how disaster risk is impacting households in cities in SSA. Risk informed city planning and significant investments in public services, such as solid waste management and drainage are needed to meet the challenges of rapid urbanization, urban poverty and climate risk. Much of the responsibility fall on city and local governments that have limited capacity and fiscal space to meet the investment needs. Quantifying the cost of flood exposure for households opens opportunities to inform land-based financing and disaster risk management policy. This study does this quantification by using a hedonic price approach to evaluate the relationship between flood impact and rent pricing in Accra (Ghana), Addis Ababa (Ethiopia), Antananarivo (Madagascar), and Dar es Salaam (Tanzania). Although crucial for SSA countries and for low- and middle- income countries more generally, this type of analysis is scarce in the development economics literature.

Climate change is expected to increase the frequency and intensity of floods (IPCC, 2014). Severe and moderate floods can cause population displacement, water-borne diseases (Bartlett, 2008), and food insecurity; destruction or deterioration of assets, property, and public infrastructure; loss of income and lives; disruption to economic activities, school attendance, and transport networks; electrical energy and water outrages, etc. Other things being equal, the higher the concentration of population and assets, the higher the value of the loss, which makes urban areas especially vulnerable.

Ability to quantifying the cost of avoiding flood would help policy makers to conduct cost-benefit estimations of investment in flood resistant infrastructures and contingency plans. Reducing exposure to disasters in a given area of a city shines a spotlight on the importance of location and can make certain areas more attractive for new residents, businesses, and amenities – all dynamics that increase the value of the land. This provides an opportunity for local authorities to capture the land value to pay for projects that will increase resilience to natural disasters, or to finance other public priorities. However, we lack the tools to forecast land value appreciation from disaster mitigation investments and studying whether or not land pricing internalizes flood risks would facilitate development of such tools.

Hedonic property price models can be used to capture the value of avoiding flood exposure. They enable estimation of property prices based on bundles of housing, amenities, and location characteristics (Bishop et al., 2020; Brueckner, 2011; Rosen, 1974). In an efficient housing market, properties exposed to flooding are expected to have a lower price tag than equivalent properties not exposed to flooding. This price discount can be interpreted as the welfare cost of flood exposure, or in other words the willingness to pay to avoid flooding. Numerous studies which focus on high- or middle- income countries use hedonic price models to calculate the property price discount for location in an area exposed to flooding.[1]

This study is one of very few analyses of the relationship between flooding risk and rents in low- and lower-middle income countries. Meta-analysis of 37 published papers and 364 point estimates shows that all of them focus high-income countries, mainly the United States (Beltrán et al., 2018). These meta-regressions show that properties located in flood plains which suffer from inland flooding are 4.6 percent cheaper on average than a similar property not exposed to flood risk. However, the effects of flooding on property prices in the 37 papers studied by Beltrán et al. (2018) vary between a 75.5 discount to a 61 percent price premium. Thus, their study finds very high levels of heterogeneity between the effects of flooding on property prices even in an efficient housing market.

Examples of studies of the relationship between the housing market and flooding in upper-middle-income economies include Rabassa and Zoloa (2016), and Álvarez and Resosudarmo (2019) who study La Plata, Argentina, and Jakarta, Indonesia respectively. Rabassa and Zoloa (2016) estimate the benefits of a new hydraulic infrastructure based on estimation of the willingness to pay to avoid flood exposure using data on real estate prices and a flood risks map. They find that flood plain areas have a 3.5 percent price discount compared to other areas, and that this discount can be five times higher in areas of higher flood risk and less resilience. Álvarez and Resosudarmo (2019) measure the correlation between the water level of floods in Jakarta in 2007 and housing rental prices and find that a 10 percent increase in the flood depth is associated with 1.24 percent lower rents. Using the same data sources as this study, Erman et al. (2020) and (WB, 2017) assess the relationship between rents and reported flood exposure in Accra, Ghana and Antananarivo, Madagascar respectively. Erman et al. (2020) identify a 27 percent price discount on rent among flood-affected households in Accra and (WB, 2017) find that flood-affected households pay 15 percent lower rents in Antananarivo, Madagascar.

Most of the literature uses hazard maps to identify flood plains or high-risk locations. For instance, Bin and Polasky (2004) look at both location within a floodplain and location outside a floodplain in Pitt County, North Carolina, US which was severely impacted by the major floods that followed hurricane Floyd in 1999. They find that properties located in floodplains were cheaper than equivalent properties located in other areas, and that the price discount in floodplains was significantly larger after the hurricane.

This study uses self-reported data from household surveys to assess the willingness to pay to avoid floods. The analysis relies on four household surveys conducted between 2016 and 2018 in four SSA cities that are the most economically and politically relevant in their countries: Accra, Antananarivo, Dar es Salaam, and Addis Ababa. Flood risk is captured in two ways: by having reported being affected by a flood in recent years and respondents' perceived risk of future flooding. The use of household survey data provides an opportunity to expand the use of the hedonic pricing approach to evaluate the benefits of urban resilience and infrastructure investment in countries that rely heavily on household survey data and where hazard risk and property value data may not be readily available. The household survey data are complemented by information on access to jobs.

[1] See Beltrán et al. (2018) for an extensive review of the effect on property prices of housing location in a flood plain.

The results show that rents tend to be lower in areas exposed to flood risk in three of the four cities. The relationship between job density and rents is less clear, which is most likely a result of the nature of city shape and the role of informal job markets. However, job density seems to play a role in the household decision to settle in high risk areas.

Overall, the study indicates that the drivers of rents in cities in SSA are still poorly understood and that lack of data is the main barrier to a better understanding. This analysis shows that household surveys that include rent or housing costs, housing characteristics, access to public services, tenure arrangements, and household experiences with flooding or other natural hazards are an important source of information in developing countries to value the willingness to pay to avoid hazard risk, and thus, the benefits associated to risk reduction investments. In housing markets with no or limited access to information about flooding risks, surveys with information on the experience of households with flooding and their expectation of future floods capture better the internalization of flooding risks by households than modeled flood maps.

The remainder of the paper is organized as follows. Section 2 provides a general overview of the flood and vulnerability contexts in the cities studied. Section 3 introduces the data and the empirical estimation strategy. Section 4 presents the empirical results. Section 5 concludes the paper.

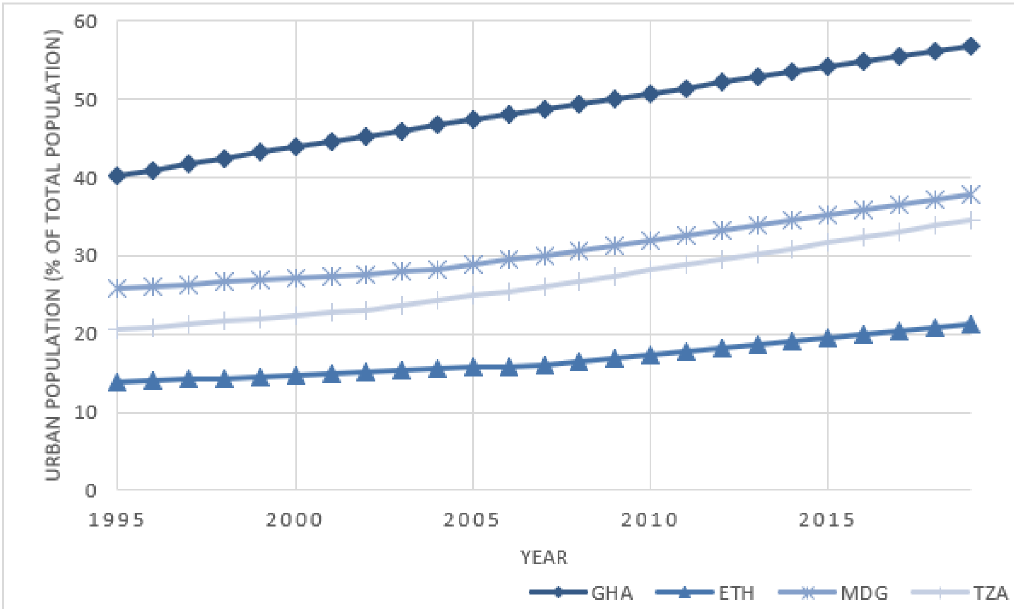
2 Urbanization and vulnerability to floods in four Sub-Saharan African cities

Urbanization is associated with development, higher incomes, better access to employment, better public services, and better access to information. However, if the urbanization growth rate exceeds the rate of development, or is accompanied by poor quality institutions, urbanization can increase population inequality. This results in poorer people being more exposed to poor infrastructure, low quality housing, and natural hazards. In particular, some urban conditions such as high population and asset densities, unplanned settlements, low quality drainage systems, unimproved solid waste management, poor housing conditions, and certain kinds of locations (coastal areas, lowland, near to rivers) increase the risk of exposure to natural hazards.

The share of Africans living in urban areas is projected to grow from 42 percent in 2018 to 59 percent in 2050 (UN, 2019). This share is the lowest among world regions. However, after 2020 the urbanization growth rate in Africa is likely to be the highest in the world, overtaking rates in Asia. Among the countries studied, Ghana has the highest urban population rate (57 percent) and has experienced the highest urban population increase since the mid-1990s (+18 percentage points). It is expected that almost three-quarters of Ghana's population will be urban in 2050. Madagascar and Tanzania have experienced similar urbanization rates, with urban population shares in 2020 of 38 percent and 35 percent respectively, expected to increase to 58 percent and 55 percent by 2050. Ethiopia has experienced a slower pace of urbanization and in 2020 had an urban population share of 22 percent although this is expected to almost double by 2050 (see Figure 1 and Table 1).

This paper studies the largest and most important cities in each country: Accra, Antananarivo, Dar es Salaam, and Addis Ababa. The cities make up between 15 (Accra) and 31 percent (Antananarivo) of each country's urban population (Table 1).

FIGURE 1: Urban population share evolution



Source: Authors' calculation based on World Development Indicators

TABLE 1: Urbanization, poverty, and floods

	Ethiopia	**Ghana**	**Madagascar**	**Tanzania**
Country				
total population, 2019 (millions)[1]	112.1	30.4	27.0	58.0
urban population share, 2020 (%)[1]	21.7	57.3	38.5	35.2
projected urban population share in 2050 (%)[2]	39.0	73.1	57.9	55.4
City				
total population, 2018 (millions)[2]	4,400	2,440	3,058	6,048
% on total urban population, 2018 [2]	20	15	31	30
Poverty rate at international poverty line population below $1.90 a day (%)[3]	30.8	12.7	78.8	49.4
Floods 2013-2017[4]				
number of events	3	2	2	8

[1] World Development Indicators.
[2] UN (2019).
[3] Reference years: Ethiopia: 2015; Ghana: 2016; Madagascar: 2012; Tanzania: 2017.
[4] Dartmouth Flood Observatory. Floods are defined in three categories: class 1, large flood events, significant damage to structures or agriculture, fatalities, and/or 1-2 decades-long reported interval since the last similar event; class 2, very large flood events, more than 20 years but less than 100 year recurrence interval, and/or a local recurrence interval of at 10-20 years; class 3, extreme events, with an estimated recurrence interval of more than 100 years.

The combination of rapid urbanization, urban poverty, lack of investments in infrastructure and public services, as well as climate change, has made SSA cities increasingly vulnerable to impacts of flooding and other natural hazards. Dartmouth Flood Observatory (DFO) data consider flooding as a major event involving at least significant damage to structures and agriculture, fatalities, and displacements. In the five years preceding the survey all four countries suffered at least two such flood events and Tanzania suffered eight (Table 1). Major events such as those reported by DFO are well-documented and their impacts are captured in official numbers reported by news and governments. In addition to larger flood events, these cities are also affected by high-frequency, low-intensity flooding. The high frequency floodings are less costly in terms of direct losses but are highly disruptive to the everyday lives of residents affected by them. Floods affect people's lives in many ways. They damage assets, such as furniture, electronics, and vehicles with high replacement values for urban poor. Flooding can disrupt infrastructure, such as road networks, water, and energy services, which affects residents' ability to access jobs, school and operate an enterprise. Flooding also has health consequences and can lead to the spread of water-borne diseases, urinary tract infections, skin fungus, etc. Although both poorer and richer areas are affected by flooding, the vulnerability of housing structures and lack of access to insurance, savings and other financial support, poorer households are worse off when affected by flooding. In many cities, informal settlements also tend to be in flood plains because these areas were previously undeveloped and perhaps offered other benefits, such as proximity to jobs and services.

Since climate change is likely to make flood events more frequent and intense and the urban poor are likely to suffer disproportionately, poverty rates can be expected to increase as a result (Hallegatte et al., 2020). This is particularly important to consider in the context of the current global pandemic which is affecting urban populations disproportionately. These are important issues which need to be addressed in combination.

3 Data and methodology

3.1 The surveys

The analysis relies on integrated and harmonized data from four surveys, covering the four cities of Accra, Antananarivo, Dar Es Salaam, and Addis Ababa. For Accra, Dar Es Salaam and Addis Ababa the Disaster-poverty survey data is used, which contain information on how households experience floods, their perceived risk of future floods, and characteristics of household members, housing conditions and public services, and proxy for household expenditure, rent and housing costs. For Antananarivo, a Living Standards Measurement Survey (LSMS) is used, which covers similar variables and was therefore added to the study. The surveys were conducted in 2016 (Antananarivo), 2017 (Accra, Dar es Salaam, Addis Ababa), and 2018 (follow-up in Dar es Salaam).

To define flood exposure, self-reported information from the surveys is used. The Accra and Antananarivo surveys capture information on specific disasters (severe flooding in 2015 in Accra, and Cyclone Chedza in 2015 in Antananarivo). In the other two cities, the surveys focused on frequent flood exposure rather than a specific disaster.[2] Households were asked also about their perceived risk of future flood

[2]However, in Dar es Salaam, a follow up phone survey was conducted in 2018 to capture information on the flood experienced in that year.

exposure.[3] Both variables are used in the analysis to proxy exposure to flood risk by using two binary variables: 1) if the household reports having been directly affected by floods, and 2) if the household perceives the risk of future flood exposure as high or very high. Appendix Table A.1 provides the precise questions and the definitions of the flood exposure variables for each city. Self-reported disaster data have two main advantages. First, they capture actual household experiences and expectations rather than modeled risk estimations. Flood impacts can differ from street to street depending on elevation, housing quality, access to, and topography, etc., and flood models do a generally poor job of capturing localized flood risk, especially in urban areas.[4] Second, in the context where information on flood risk as defined in flood maps is not readily available, up-to-date or well-known to the public, past experiences of flood and the perception of risk can be better predictors of rent values. The use of self-reported proxies for flood risk may therefore increase the accuracy of hedonic models when used in contexts where buyers (or renters) are not fully informed.

In hedonic analyses, house-transaction prices are ideal to define housing value (Bishop et al., 2020). However, they can be difficult to access even in developed countries. Bishop et al. (2020) provide a list of the countries where microdata on housing transactions is available: it includes several European countries, the United States, Australia, Chile, China, Japan, and the Republic of Korea. Examples of studies that use transaction data in middle-income countries are Argentina (Rabassa and Zoloa, 2016) and Indonesia (Álvarez and Resosudarmo, 2019). Limited data availability explains why, while the hedonic approach to estimate households' willingness to pay for a change in an environmental amenity is used extensively by researchers, it is difficult to find studies of African countries. Household survey data overcome this limitation since surveys often capture information needed to construct a hedonic pricing model, including housing characteristics, access to services and different determinants of housing costs. The surveys exploited in this study include detailed questions on actual housing costs and rents and an estimate of how much a tenant would pay in rent for the dwelling if rented, as estimated by the respondent. Since only a subset of households are renters, exploiting the "self-estimated" rental values helps increase the sample size. The analysis therefore combines reported rent values and the self-estimated rent values[5] to construct a rent value variable for all four cities. Observations with missing values for both items were excluded. Comparison of the rents, self-estimated rents, and the combined variable distributions are depicted in Appendix Figure B.1. Measurement errors can affect rent and self-estimated rent values. To reduce these errors, outliers were removed and replaced with estimated values.[6] Values are in local currency and transformed to 2017 PPP US$.

The final sample is based on observations without missing values for rents and self-estimated rents. It includes 3,132 households in four cities and four countries: Accra (996 households), Antananarivo (919 households), Dar es Salaam (466 households), and Addis Ababa (751 households). Table 2 presents a summary of the different database characteristics. More detail on the survey methodology and char-

[3]The questions related to flood perception were almost identical for all four cities although for Antananarivo the time horizon was 5 rather than 2 years.

[4]In most studies, flood models or risk area identifications (Beltrán et al., 2018) are large surfaces.

[5]The question related to self-estimated rent is "If somebody else wants to rent a dwelling just like this today, how much money would he/she have to pay monthly?"

[6]Outliers are defined as observations that deviate from the mean by three standard deviations or more. Outliers were replaced by estimated rents/self-estimated rents. Rents/self-estimated rents are estimated based on data on expenditure, housing conditions, access to public services, and time to business center. Outliers represent 0.5% to 2% of observations, depending on the city.

acteristics for Accra, Dar es Salaam, and Antananarivo can be find in Erman et al. (2020), Erman et al. (2019), and WB (2017) respectively.

TABLE 2: Databases descriptions

City	Database	Area	Date	Flood/s	HH selection method
Accra	Disaster-Poverty household survey	9 neighborhoods considered slum areas in the Odaw basin area	May-Jun/2017	2015 flood	4 strata: combination of high/low risk of flood and high/low level of poverty. Informal settlements. Not representative at the city level.
Antananarivo	Urban Living Standards	Greater Antananarivo	Oct-Dec/2017	2015 flood "Chedza flood"	2 strata: risky and no risky areas, where risky are EAs affected by Chedza. Representative at the city level.
Dar es Salaam	Disaster-Poverty household survey	Dar es Salam	Nov/2017, Sep/2018	Most recent flood, 2018 flood	3 levels of flood risk (no risk, low risk and high risk). Representative at the city level.
Addis Ababa	Disaster-Poverty household survey	Addis Ababa	May-Jun/2017	Most recent flood	Representative at the city level.

3.2 Accessibility to jobs

In an efficient housing market, property prices rise with increased access to jobs and amenities (Ahlfeldt, 2013), and in choosing where to live people make a trade-off between low housing value and proximity to jobs. To understand rents, we need to understand access to economic opportunities and how it influences housing markets. However, there are two significant data constraints, common to developing country cities which make it difficult to capture access to economic opportunities, particularly for SSA cities: 1) lack of information on job locations, and 2) lack of information on transit routes and travel times (Peralta-Quiros et al., 2019). This study captures access to economic opportunities using the spatial density of employment developed in Barzin et al. (2022). This measure is used to proxy for job density. It was created using a machine learning based algorithm, and data from OpenStreetMap (OSM) and Google Earth Engine (GEE). OSM data provide information on the location of different types of public and private services and institutions (hospitals, pharmacies, banks, schools, etc.), amenities (rivers, parks, etc.), and infrastructure (roads, airports, etc.). GEE data were used to add information on population density, intensity of night lights, and land cover. This is a novel way to estimate job density. The main advantage of this proxy is that it can be calculated for any city which has accurate and available OSM and GEE data and where data on economic activity are scarce or missing. It allows comparison of economic activity across cities, based on a unique measure. The job density proxy measures relative job density where a low value denotes lower job density and a high value higher job density. The values themselves cannot be interpreted directly. The maps of the four cities analyzed here, and with the spatial distribution of jobs are provided in Appendix Figures D.1 to D.4.

3.3 Descriptive statistics

Thirteen percent of households in our sample had been affected directly by at least one flood event: 44 percent in Accra, 9 percent in Antananarivo, 20 percent in Dar es Salaam, and 8 percent of households in Addis Ababa. In Accra and Dar es Salaam, the proportion of households that perceived risk of future flooding to be high is similar to the proportion of households actually affected by flooding. In contrast, the proportion of households in Antananarivo and Addis Ababa which perceived future flooding risk as high was much higher than the proportion of households actually affected by floods (Table 3). This suggests that these households are in flood prone areas but have not been affected by floods in recent years.

The share of households in the sample that report owning their dwelling is 15 percent in Antananarivo, 20 percent in Accra, and 52 percent in Addis Ababa (Appendix Table D.1). Renters represent 44 percent in Accra, 34 percent in Antananarivo, 36 percent in Dar es Salaam, and 42 percent in Addis Ababa of the total sample (Appendix Table D.1). All renters are considered in the sample used for analysis. Since the variable used for analysis combines reported rent value and self-estimated rent, the sample used for analysis also consists of households in other tenure arrangements. In the case of Dar es Salaam, combining rents and self-estimated rents does not increase the number of observations since only renters responded to the rent estimation question.

In SSA cities, ownership does not necessarily equate with tenure security. Families often consider themselves owners although they may not have legally recognized rights to occupy the dwelling and/or the land. In Accra 29 percent of households in the sample are "rent free". The "rent-free" dwellings are mainly owned by household relatives that are not household members (92 percent).

Access to public services is generally low. In Antananarivo, only 6 percent of households have access to improved toilet facilities and 17 percent have access to improved drinking water. The dwellings have an average of between 1.5 (Accra) and 3.1 (Addis Ababa) rooms. In terms of rents, households in Addis Ababa pay the highest average annual rents in the sample, and households in Accra pay the lowest (Table 3). In all the cities considered, there is a high concentration of low rents. However, Antananarivo and Dar es Salaam have a flatter distribution of higher rents compared to Accra and Addis Ababa (Figure 2).

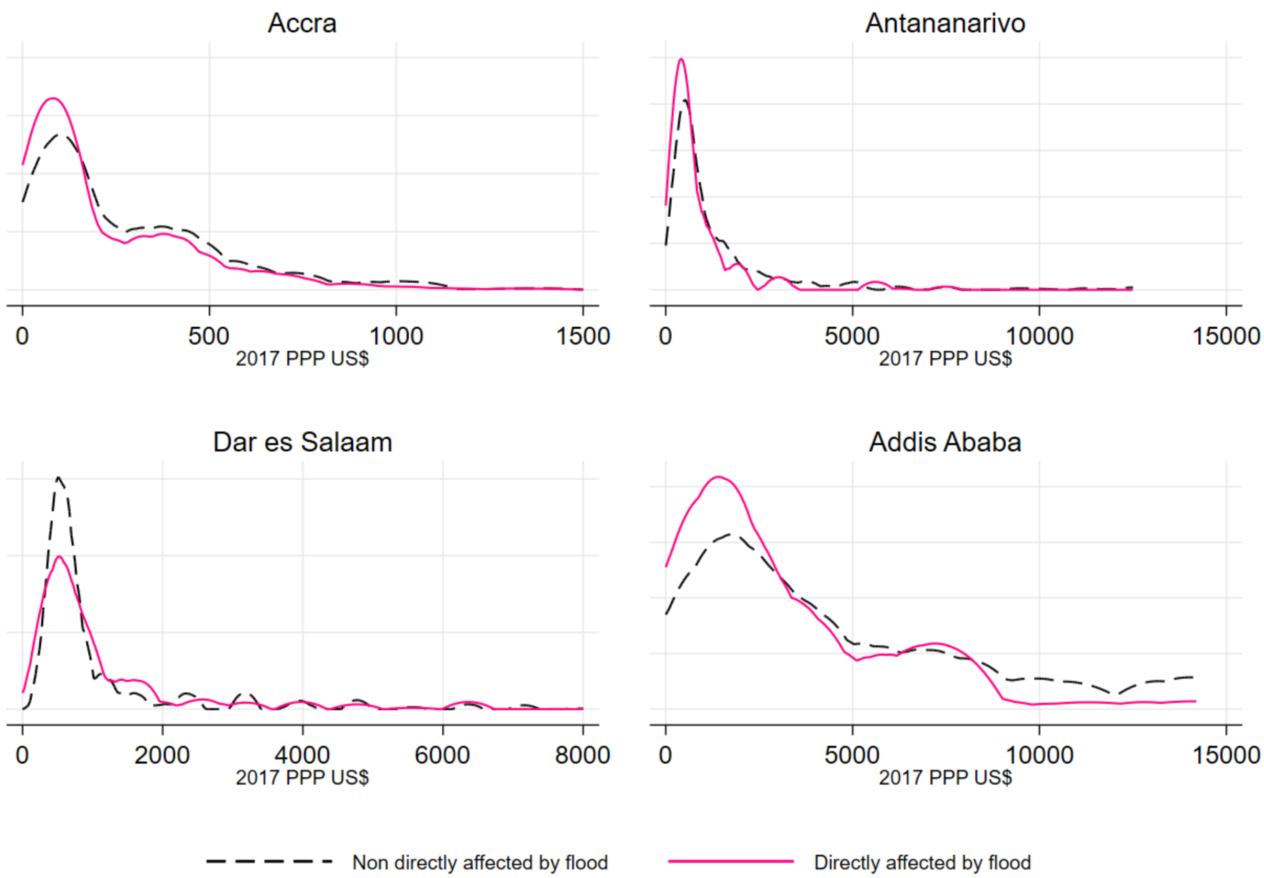
Among the surveyed households, those in Accra have the lowest estimated job density, and those in Antananarivo and Dar es Salaam have the highest.

TABLE 3: Descriptive statistics by city

	Accra		Antananarivo		Dar es Salaam		Addis Ababa	
	Obs	%	Obs	%	Obs	%	Obs	%
Exposure to floods								
Households directly affected by flood	996	44.5	919	9.1	466	19.6	751	8.4
Households that perceive flood risk as high	996	40.2	919	51.1	466	17.7	751	31.2
Dwelling tenure	996		919		466		751	
Owner	202	20.3	135	14.7	0	0	386	52.5
Rented	440	44.2	781	85.0	466	100	105	44.5
Free	293	29.4	0	0	0	0	15	2.6
Other	61	6.2	3	0.3	0	0	1	0.4
Housing conditions								
Access to improved toilet facility	996	15.6	919	6.0	466	26.4	751	26.6
Access to improved drinking water	996	45.3	919	17.1	466	34.9	751	98.0
Access to collected solid waste	996	73.9	919	65.3	466	88.6	751	66.6
Lighting with electricity	996	96.7	768	99.2	466	91.9	751	99.5
	Obs	Mean	Obs	Mean	Obs	Mean	Obs	Mean
Household size	996	3.4	919	4.1	466	3.2	751	4.3
Number of rooms	996	1.5	919	1.7	370	2.6	751	3.1
Annual rent								
Rent (2017 PPP US$)	482	463.6	785	895.8	465	1072.2	156	1871.9
Self-estimated rent (2017 PPP US$)	979	106.8	134	4081.6	466	1142.1	708	4727.9
Combined rent and self-estimated rent (2017 PPP US$)	996	258.3	919	1372.8	466	1077.9	751	4126.1
Job density	817	1.5	916	2.0	466	2.0	751	1.7

Notes: Figures are weighted.

FIGURE 2: Distribution of annual rent by flood exposure



Source: Authors' calculation based on Disaster-Poverty Household Survey.
Notes: The rent variable is a combination of the rents declared by households and their estimations of rent values. Rent is measured in 2017 PPP US$by year.

3.4 Empirical method

The aim of the study is to understand the willingness to pay to avoid floods among households in four SSA cities. To this end, this study employs a hedonic pricing approach (Rosen, 1974) to assess drivers of rent values. In a hedonic regression the price of a dwelling is determined by a bundle of internal housing attributes, housing location, amenities, transport costs, and other determinants of life quality (Bishop et al., 2020; Brueckner, 2011). The estimated coefficients in the hedonic regressions represent the share of the price for each attribute. The hypothesis of this study is that dwellings that are exposed to flooding have a lower price than dwellings located elsewhere. The hedonic model isolates the effect of flood exposure on housing prices from other drivers and therefore reflects the price that residents assign to safety from floods. The following econometric specification is used:

$$\ln Rent_i = \alpha_0 + \alpha_1 flood_i + \alpha_2 T_i + \alpha_3 \mathbf{H}_i + \varepsilon_i \tag{1}$$

where i indexes the household, $Rent$ is the rent value, $flood$ is the previous exposure to floods or high perception of risk of future flooding, T is job density, $\mathbf{H}$ is a vector of housing characteristics, and ε is the error term.[7] If the housing market is efficient then all else being equal, we would expect $\hat{\alpha}_1 < 0$ and $\hat{\alpha}_2 > 0$.

The hedonic model assumes perfect competition. This is a bold assumption considering the high level of informality in the cities analyzed. For example, perfect competition in housing markets assumes that clients are fully informed, the price is set by the market, and zero transaction costs. However housing markets are usually not perfectly competitive, especially not in developing countries. For example, information that can affect housing pricing may not be available or difficult to access. This is particularly true regarding hazard risk information. As a result, unless an area has been recently flooded, residents may not know that an area is flood-prone. Information on pricing may not be readily available either. In more informal housing markets, where there is a lack of trust and legal protection, prices are often set in informal networks, such as extended family or within religious or ethnic groups. Transaction costs are not zero. Large down payments are common in informal housing markets, as a way for landlords to protect themselves. Despite these challenges, the hedonic pricing model has been used extensively to estimate the willingness to pay for changes in environmental amenities and to inform public and private decision makers (Bishop et al., 2020). By controlling for other possible drivers of housing costs in the context of African cities, the analysis reduces part of the potential bias. However, it is important to keep these drawbacks in mind when interpreting the results of this study.

[7] Bishop et al. (2020) recommend that in selecting an econometric specification 1) the price function should be assumed to be nonlinear, and 2) the estimations should rely on robust standard error and be clustered at the spatial scale of the variable of interest to account for heteroskedasticity and spatial autocorrelation. The analysis in this paper takes account of these recommendations.

4 Results

4.1 Flood risk and rent

Appendix Tables C.1 to C.4 present the estimations of Equation (1) for previous flood exposure and perception of future flood risk and for each city separately. Figures 3 and 4 illustrate the modeled impact of flood exposure and perceived flood risk, respectively, on annual rent, based on estimations (7) and (8) in Tables C.1 to C.4. The diamond represents the average marginal willingness to pay to avoid flood risk as a percentage of the annual rents in each city,[8] while the tails correspond to the confidence intervals.

The hypothesis of $\hat{\alpha}_1 < 0$ in Equation (1) holds true in Accra, Antananarivo, and Addis Ababa for both definitions of $flood$. In Antananarivo and Addis Ababa it is significant when measured using previous exposure to flooding and in Accra, the relationship is significant when flood risk is measured using the perception of future flood risk.. Generally, the estimates for the marginal willingness to pay to avoid flood risk is 14 percent (Accra), 14 percent (Antananarivo), and 56 percent (Addis Ababa) of annual rent values.

The findings for Dar es Salaam are less intuitive. A higher perceived risk of future flooding is associated with a 28 percent higher rent and previous exposure to flooding is associated with 9 percent higher rent (although the latter result is not statistically significant). Using the same dataset, Erman et al. (2019) also found that past exposure to flooding is associated with higher reported rents, but they also found that affected house owners consistently value their dwelling at a lower price than non-affected households (32 to 36 percent lower). The non-intuitive relationship between rent and flood risk found in this study is most likely caused by a combination of 1) lack of transparency of what areas are flood-prone, 2) high transaction costs for renters and 3) omitted variable bias. In terms of awareness about flood risk, only 12 percent of households report having been aware of the flood risk when they moved into the area. Among the 78 percent that provided a down payment to access the rental, 80 percent report that it covered more than six months. As a result, many of the households may face barriers to leave the dwelling even after they realize it is located in a flood-prone area. On omitted variable bias, it is possible that flood risk is associated with other characteristics that can make an area more attractive, such as aesthetics, air quality, community engagement, proximity to green spaces, universities, or other amenities that can influence rents and that the model is not controlling for. These characteristics may influence rents more than exposure to flooding since a household may decide to make the trade-off of accessing more amenities at the "expense" of facing higher flood risk, knowing that renting is temporary. Other studies have found a positive relationship between flood risk and housing values. For instance, in Bin and Kruse (2006) flood risk reduces property values in inland areas but increases values in coastal areas.

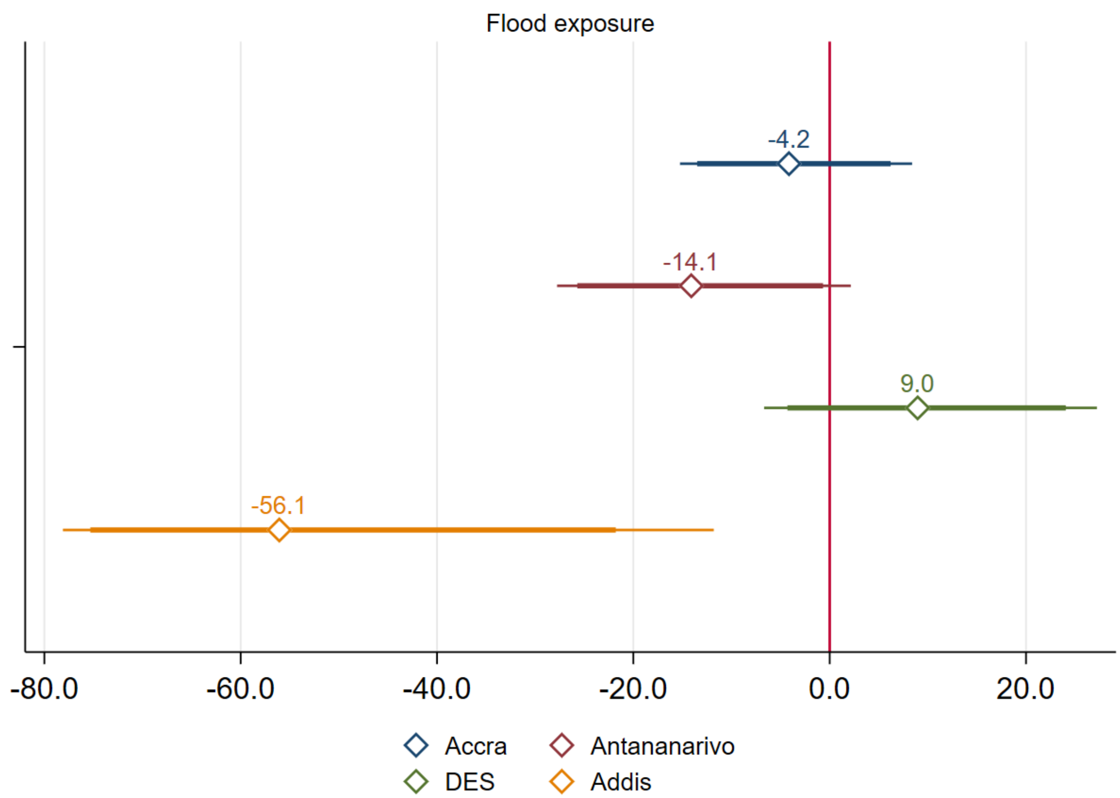
The results for Accra and Antananarivo are sensitive to the exclusion/inclusion of tenure status (owner, renter, free housing, other) and tenure agreement (non-agreement, written and non-written agreements). The explained rent variance (R^2) increases by 47 percentage points and 23 percentage points for Accra and Antananarivo respectively when including tenure variables.[9] In the case of Accra, Erman et al. (2020) show that exposure to floods is associated with 27 percent lower rents. The difference

[8]The marginal effects of the dummy variables are calculated as ($\exp^{\beta_i}$-1), where β_i is the estimated coefficient of the variable.

[9]For Accra an increase of 27 percentage points is attributed to tenure type, and 20 percentage points to tenure agreement. For Antananarivo, the total increase is attributed to the inclusion of tenure agreement.

between the results in this study and those in Erman et al. (2020) are that their specifications focus only on renters and they did not account for tenure agreements. When not including tenure arrangements (see columns (1) to (6) in Appendix Tables C.1 to C.4), estimates are more consistent to Erman et al. (2020) finding that exposure to floods is associated with 21 percent lower rents and higher perceived flood risk is associated with 27 percent lower rents (columns (1) and (2) in Appendix Table C.1). The result emphasizes the close relationship between flood risk and tenure in these cities. The estimates for Antananarivo are consistent with a previous study which used a similar approach with the same data (WB, 2017), despite some specification differences.[10]

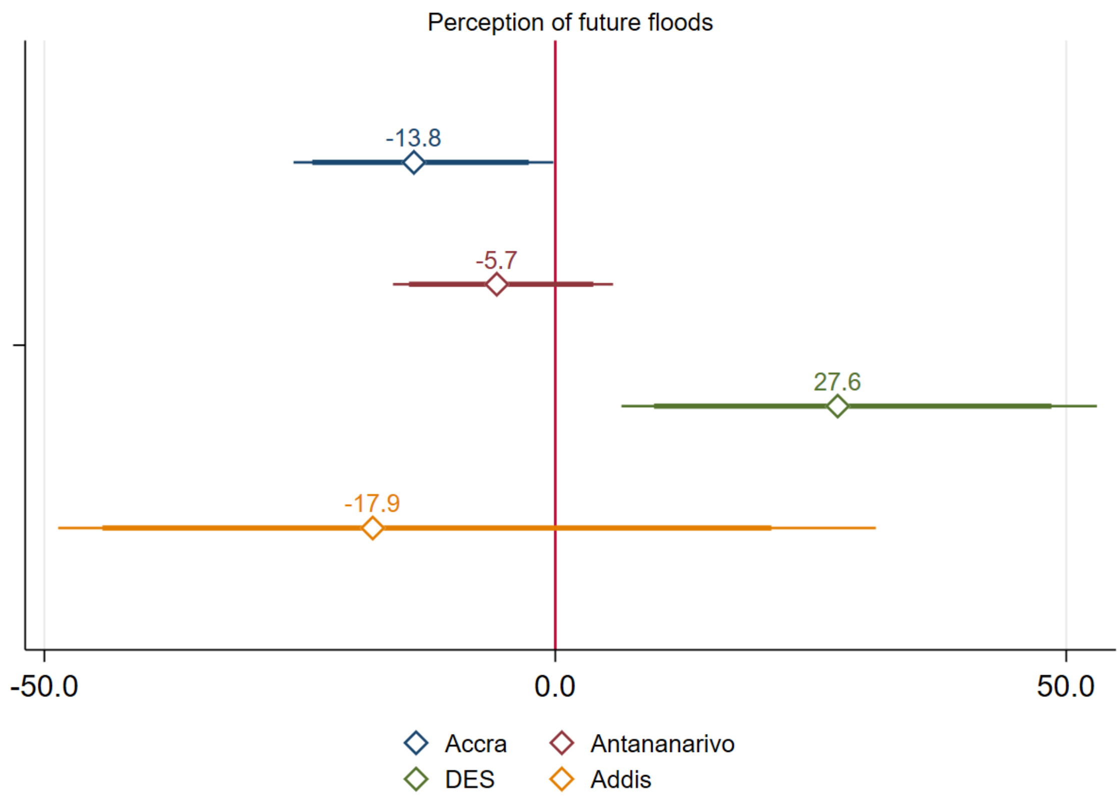
FIGURE 3: Marginal effect of flood exposure on annual rent



Notes: The diamonds denote the marginal effects of exposure to flood as percentages of annual rents (Appendix Tables C.1 to C.4, column (7)). The thick line is 90% Confidence Intervale and the thin line is 95% Confidence Intervale.

[10]In WB (2017), the dependent variable is rent and is defined only for renters. Flood exposure is defined at the enumeration area (EA) level. The definition of flood risk exposure combines information on EA identified as being "at risk of floods" if more than 2.5% if its population were affected by the Chedza floods, and household in the EA that declared been affected by Chedza.

FIGURE 4: Marginal effect of flood perception on annual rent



Notes: The diamonds denote the marginal effects of higher perceived risk of future flooding as percentages of annual rents (Appendix Tables C.1 to C.4, column (8)). The thick line is 90% Confidence Intervale and the thin line is 95% Confidence Intervale.

4.2 Access to jobs and rents

A job density proxy was measured based on spatial data of the economic activity distribution (Barzin et al., 2022) and added to the model to assess the relationship between rent and access to jobs. Better access to jobs tends to be associated with higher rents and housing costs so it is therefore assumed that $\hat{\alpha}_2 > 0$ in Equation (1). Figure 5 presents the value of the marginal effects of job density on rents in percentage, based on estimations including the variable exposure to actual floods (Appendix Tables C.1 to C.4, column (7)).

In Accra and Addis Ababa, areas with higher job density are associated with lower rents. These results are contrary to our hypothesis. In Accra, while some expensive dwellings located in the north-east of the Accra district, have relatively high job density, many households living in more expensive dwellings in the south-west have relatively low access to jobs. These households in the south-west could be driving the results (Appendix Figure D.1).

In the case of Addis Ababa, the highest job density is around the Ketema district, a populous area with low rents and improvised settlements, that means rents are lower in the economic center, and higher in the periphery. Two of the richest locations in Addis Ababa are close to the airport, and close to the African Union, respectively two and one hours travel time from the economic center (see Appendix Figure D.4).

In Dar es Salaam, the relationship between job density and rents is also negative but not statistically significant.

In Antananarivo, areas with high job density have higher rents, on average. WB (2017) also found that rents close to the city center were higher. The result is intuitive also since Antananarivo is a relatively monocentric city, where jobs are concentrated in the center (see Figure D.2)

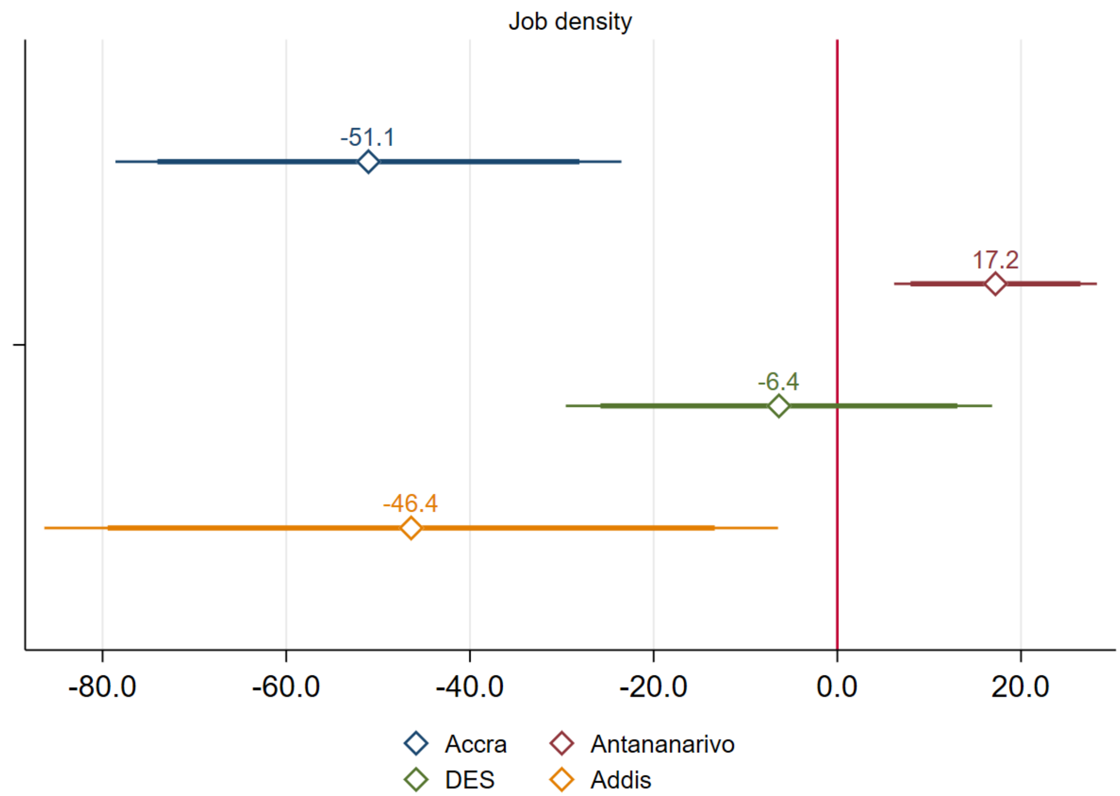
Since the variable we use to measure job density is non dimensional, it is difficult to interpret a marginal increase, but the results show that the relative importance of job density on rents is highest in Accra compared to the other three cities.

To check for a relationship between flood risk and access to jobs, we interact the proxy for job density with the variables measuring flood risk for each city (Appendix Tables C.1 to C.4, columns (5) and (6)). The negative effect of job density on rents is higher (in absolute value) when flood risk is high in Accra and Addis Ababa, and the positive effect of job density on rents becomes negative when flood risk is high in Antananarivo.[11] The relationship is not found in Dar es Salaam. This finding seems to suggest that access to jobs is an important factor driving people to settle in flood-prone areas since residents in all but one city face a significant discount when renting dwellings in flood-prone areas that are also close to job opportunities. Kocornik-Mina et al. (2020) analyze large urban floods in 40 countries, mostly developing countries, and find that low elevation areas experience flooding more frequently and that they also concentrate a higher density of economic activities.

However, the findings also show that job density is linked to lower rents in three of the four cities studied (although in Dar es Salaam the result is not significant), indicating that the most economically active areas are not necessarily the most attractive for households. While the job density proxy is based on access to amenities, services, and infrastructure, it does not account for the quality of the same, which

[11] A Wald test for the joint significance of the interaction term was conducted; the only non- statistically significant interaction term was for Dar es Salaam, for the interaction between job density and actual flood exposure (Appendix Table C.3, column(5)).

FIGURE 5: Marginal effect of job density on annual rent



Notes: The diamonds denote the marginal effects of job density as percentages of annual rents (Appendix Tables C.1 to C.4, column (7)). The thick line is 90% CI and the thin line is 95% CI.

could influence the result. There are also factors that could be associated with job density that may make a place less attractive that we are not controlling for, such as crime rate, air and water pollution, and access to recreational opportunities. So, while these factors could be driving rents down in economically active areas, our analysis also shows that high flood risk is driving it down even more.

4.3 Other factors influencing rents

The results for housing conditions (Appendix Tables C.1 to C.4 and Figure 4) show that as expected, in all four cities the higher the number of rooms (a proxy for housing size), the higher the rents, and that this effect is decreasing with the number of rooms. Unimproved houses (such as like improvised and/or shared/compound houses, tents, shacks) are associated with lower rents. Other factors such as improved wall and floor materials, electric lighting, and toilet facilities are associated with higher rents. In the case of access to public services, rents are, on average, higher for dwellings with access to solid waste collection and improved water sources. There are some heterogeneities concerning the relevance of each determinant across cities but with the exception of improved roofing materials, the results are in line with expectations. These findings suggest that rent value, as measured in this study, is a good predictor of housing quality, and that the hedonic approach can be considered appropriate to analyze these SSA cities.

TABLE 4: Results on housing conditions

	Accra	Antananarivo	Dar es Salaam	Addis Ababa
Number of rooms	(+)	(+)	(+)	(+)
Number of rooms squared	(-)	(-)	(-)	(-)
Unimproved house	(-)	N.S.	(-)	(-)
Unimproved roof material	(+)	N.S.	N.S.	N.S.
Unimproved wall material	(-)	(-)	N.S.	N.A.
Unimproved floor material	N.S.	N.S.	(-)	(-)
Unimproved drinking water source	N.S.	(-)	(-)	N.S.
Unimproved toilet facility	N.S.	N.S.	(-)	(-)
Not collected solid waste	N.S.	(-)	(-)	N.S.
Electric lighting	(+)	(+)	(+)	N.S.

Notes: The direction of the correlation between rent and housing characteristics (Appendix Tables C.1 to C.4)is denoted by positive (+) and negative (-) signs for statistically significant results (at the 10% level). Rela- tionships in the expected direction are in blue and in red otherwise. NS is not statistically significant at the 10% level, NA is not applicable i.e. the variable is not included in the estimations.

4.4 Discussion of the main challenges

There are some major challenges related to assessing the relationship between flood risk and rents in the context of African cities. Some of the specifications in Appendix Tables C.1 to C.4 show a non-significant relationship but this does not mean that people are not willing to pay to avoid exposure to floods. Rather it highlights some of the remaining issues and knowledge gaps which make it difficult to capture the influence of disaster risk on housing markets in African cities.

First, tenure matters because it is linked to both housing costs and flood risk and violates the assumption of perfect markets in a hedonic regression. Unfortunately for researchers, tenure is not a binary concept but rather a range. In Accra 80 percent of owners have no tenancy/ownership agreement, but not all of them fear eviction. Fifteen percent of households report fearing eviction in the next 12 months. Informal housing markets in Accra rely on social networks. For example, for 46 percent of households, non-household relatives own the land that the dwelling is housed on. In Dar es Salaam, 74 percent of renters provided down payment. In 80 percent of cases the down payment covers more than six months. Being locked into a rental agreement with huge upfront payments increases transaction costs significantly. Tenure insecurity itself also drives vulnerability since it can discourage investment in housing quality (Nakamura, 2017), which could increase resilience to floods.

Another problem is the lack of transparency related to flood risk. As reported, in Dar es Salaam for example, only 12 percent of households directly affected by floods reported having been aware of the flood risk when they moved into their homes. Flood maps and information on flood risk are not readily available, and landlords can choose to withhold information on historic flood experiences to new tenants. In contexts where deals are made in social networks and rental properties are not being widely marketed, it becomes difficult for consumers to access information on what rents should be in different neighborhoods. As such, dysfunctional and informal housing market results in factors that would affect prices in a more functional market, such as flood risk, not being internalized.

5 Conclusions

This paper investigates the relationship between flood exposure and rents in Accra, Addis Ababa, Antananarivo, and Dar es Salaam, using a hedonic property price approach with four cross-sectional household surveys complemented with data on job density. Flood exposure is measured using self-reported information from households on whether they have been affected by flooding. Flood risk is measured with self-reported information on the perception of the risk of future flood exposure.

The results suggest that flood exposure/risk is associated with lower rents in three of the four cities studied. The willingness to pay to avoid flood exposure is between 14 percent (in Accra and Antananarivo) and 56 percent (in Addis Ababa) of average rents. In contrast, in Dar es Salaam, flood exposure/risk is associated with higher rents. The relationship between flood exposure and rents is made more complex by the close correlation between tenure and flood exposure, the lack of public awareness on flood risk, high transaction costs of housing and the importance of omitted variables, such as cultural and historical importance, presence of community networks, access to green spaces and other amenities which potentially could encourage people to move to areas with high flood risk.

The paper uses a novel way to measure access to jobs, based on data on the spatial distribution of amenities and economic activities. In Accra and Addis Ababa, rents are negatively correlated with job density, which is an unexpected finding for an efficient housing market. In Antananarivo, a more monocentric city compared with the other three cities, areas with high job density are more expensive, on average. No relationship between job density and rent is found for Dar es Salaam. When interacting job density with flood exposure/risk for each city, the negative effect of job density on rents is higher when flood exposure/risk is high in Accra and Addis Ababa, and the positive effect of job density on rents becomes negative when flood exposure/risk is high in Antananarivo. The result indicates that job access is a driving factor for households settling in flood prone areas. In addition to flood exposure/risk, it is found that housing conditions and public services are important determinants of rents. It is inherently difficult to measure flood risk using self-reported data. For example, if a binary variable is used to distinguish affected from non-affected populations, no differentiation is made between households that have experienced a one-off flood event and those that experience frequent. However, self-reported data on flood exposure have two advantages compared to frequently used flood risk maps: 1) household survey data are more often available than flood risk maps particularly in the case of data scarce environments, and 2) information on actually affected households and their expectation about the risk of future flooding are more likely to influence the value households assign to housing than data that is rarely known to the public.

The different results for different cities indicate that the ability of people to internalize flood risks through rents is context specific. This study contributes to our understanding of this issue for four cities in Africa. The findings for the relationship between flood risk and rents are economically significant despite the limits related to measuring flood risk, property pricing, and accessibility to jobs. They provide some important insights on how households assign value to amenities including flood protection, in low- income, highly informal contexts. They can help policy makers estimate the potential value that can be created by investment in flood protection measures even in the poorest areas. The results are relevant also for local governments since property taxation is usually their main source of fiscal revenue.

This study sheds light on the poorly understood relationship between flood risk and housing costs in a developing country context. It highlights drivers of housing pricing in cities that have highly informal and inefficient housing markets. As investments in urban resilience and climate change adaptation increase, the need for more research on the value of disaster risk reduction also increases. Measuring the willingness to pay of local residents to avoid flood risk is a novel and useful way to achieve this. Alongside investments in risk reduction, this study also shows that it is important to improve awareness of flood risk in cities and strengthen zoning and land use enforcement to avoid having households settle in high-risk areas. Meanwhile, it is also important to assure the availability of affordable housing with good job accessibility.

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Appendix

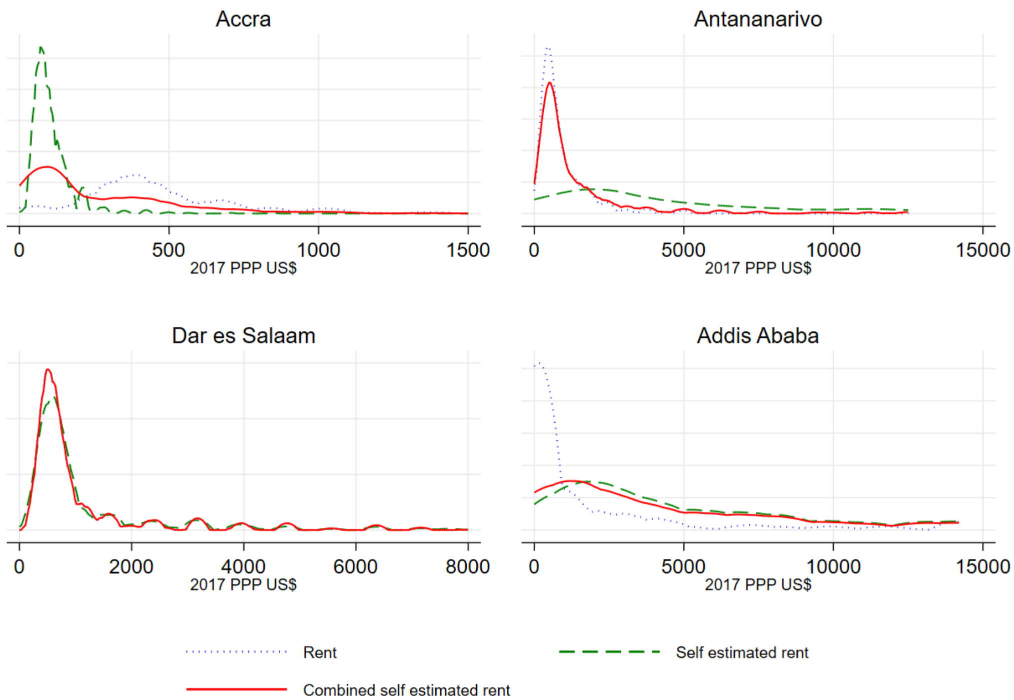
A Flood exposure and perception

TABLE A.1: Definition of being affected by flood

City	Question/s	Definition
	Flood exposure	
Accra	Were you, your household directly exposed to 2015 flood?	Directly affected: Water in the house, water and electricity services affected, loss of valuable assets, loss of income, illness, schooling of children affected, changes in food intake
Antananarivo	Was your household affected by the flooding/landslides in 2014/2015?	Answer = *Yes*
Dar es Salaam	Has water ever entered your house as a consequence of heavy rainfall/flood or have your house been damaged by flood/heavy rainfalls?	Directly affected: Water in the house, loss of valuable assets
Addis Ababa	Have you been directly exposed to flood; landslide; or fire?	If *shock = flood*: Water in the house, water and electricity services affected, loss of valuable assets, loss of income, illness, schooling of children affected, changes in food intake
	Flood perception	
Accra	In your opinion, what is the likelihood that the area where you live will be flooded anytime between now and in the next couple of years?	Answer = *Very likely* or *Likely*
Antananarivo	How likely do you think it is that your neighborhood will experience an episode of extreme flooding in the next 5 years	Answer = *Extremely likely* or *Very likely*
Dar es Salaam	In your opinion, what is the likelihood that your household will be affected by floods/heavy rains in the next 2 years?	Answer = *Very likely* or *Likely*
Addis Ababa	In your opinion, what is the likelihood that the area where you live will be flooded anytime between now and in the next couple of years?	Answer = *Very likely* or *Likely*

B Rent definition

FIGURE B.1: Distribution of rent, rent self-estimated, and combined self estimated rent



C Rent estimations

TABLE C.1: Estimation of rent, ACCRA

	Simple		Job density		Interaction		Tenure	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Directly affected by flood	-0.215*		-0.198*				-0.042	
	(0.119)		(0.112)				(0.061)	
Flood risk perception		-0.274**		-0.253**				-0.149**
		(0.111)		(0.106)				(0.073)
Job density			-0.814***	-0.789***	-0.564	-0.406	-0.511***	-0.479***
			(0.274)	(0.276)	(0.356)	(0.300)	(0.137)	(0.138)
Number of rooms	0.420***	0.396***	0.391***	0.369***	0.384***	0.345***	0.409***	0.397***
	(0.121)	(0.118)	(0.114)	(0.111)	(0.112)	(0.110)	(0.069)	(0.072)
Number of rooms squared	-0.052***	-0.048***	-0.048***	-0.045***	-0.048***	-0.042***	-0.038***	-0.036***
	(0.013)	(0.013)	(0.013)	(0.012)	(0.013)	(0.012)	(0.007)	(0.007)
Unimproved house	-0.390**	-0.378**	-0.310*	-0.302*	-0.311**	-0.323**	-0.463***	-0.461***
	(0.184)	(0.175)	(0.157)	(0.153)	(0.153)	(0.153)	(0.106)	(0.109)
Unimproved roof material	0.443***	0.438***	0.487***	0.481***	0.485***	0.471***	0.140***	0.140***
	(0.099)	(0.099)	(0.096)	(0.097)	(0.095)	(0.098)	(0.046)	(0.045)
Unimproved wall material	-0.357***	-0.356***	-0.337***	-0.337***	-0.325***	-0.329***	-0.223***	-0.215***
	(0.118)	(0.118)	(0.118)	(0.118)	(0.118)	(0.117)	(0.047)	(0.051)
Unimproved floor material	0.053	-0.018	-0.044	-0.107	-0.089	-0.155	-0.136	-0.153
	(0.279)	(0.297)	(0.234)	(0.253)	(0.220)	(0.246)	(0.095)	(0.113)
Unimproved drinking water source	-0.110	-0.114	-0.076	-0.081	-0.082	-0.092	-0.051	-0.043
	(0.097)	(0.093)	(0.097)	(0.093)	(0.097)	(0.093)	(0.048)	(0.049)
Unimproved toilet facility	-0.027	-0.039	-0.078	-0.088	-0.077	-0.077	-0.085	-0.071
	(0.110)	(0.097)	(0.111)	(0.100)	(0.109)	(0.095)	(0.075)	(0.075)
Not collected solid waste	0.121	0.097	0.097	0.076	0.103	0.094	-0.017	-0.022
	(0.110)	(0.104)	(0.110)	(0.108)	(0.111)	(0.106)	(0.058)	(0.059)

Continued on next page

Table C.1 – *Continued from previous page*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Electric lighting	0.656***	0.645***	0.581***	0.574***	0.584***	0.588***	0.210***	0.217***
	(0.178)	(0.192)	(0.172)	(0.185)	(0.174)	(0.190)	(0.067)	(0.073)
Dwelling tenure agreement								
No Agreement							ref.	ref.
Written Agreement							0.334***	0.337***
							(0.072)	(0.075)
Non-written Agreement							0.028	0.045
							(0.080)	(0.075)
Dwelling tenure status								
Owner							ref.	ref.
Rented							1.308***	1.290***
							(0.099)	(0.098)
Free							0.101*	0.092*
							(0.059)	(0.055)
Other							-0.056	-0.075
							(0.178)	(0.175)
Affected by flood					0.625			
					(0.599)			
Affected by flood $\times$ Job density					-0.552			
					(0.413)			
Flood event is likely						1.273*		
						(0.648)		
Flood event is likely $\times$ Job density						-1.020**		
						(0.448)		
Observations	817	817	817	817	817	817	817	817

R2	0.17	0.18	0.19	0.20	0.19	0.20	0.67	0.67

Note: The dependent variable is the log of rent (combined rent paid and self-estimated rent), measured in 2017 PPP US$by year. Robust standard errors are clustered at the enumeration area level. *** p<0.01, ** p<0.05, and * p<0.1.

Table C.2: Estimation of rent, ANTANANARIVO

	Simple		Job density		Interaction		Tenure	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Directly affected by flood	-0.137		-0.140				-0.152*	
	(0.107)		(0.107)				(0.088)	
Flood risk perception		-0.043		-0.044				-0.059
		(0.064)		(0.064)				(0.058)
Job density			0.164***	0.164***	0.183***	0.100	0.172***	0.172***
			(0.057)	(0.057)	(0.061)	(0.067)	(0.056)	(0.056)
Number of rooms	0.639***	0.639***	0.640***	0.640***	0.636***	0.640***	0.497***	0.497***
	(0.054)	(0.055)	(0.052)	(0.052)	(0.052)	(0.051)	(0.055)	(0.054)
Number of rooms squared	-0.039***	-0.039***	-0.038***	-0.038***	-0.038***	-0.038***	-0.032***	-0.032***
	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)	(0.006)	(0.005)	(0.005)
Unimproved house	-0.103	-0.100	-0.117	-0.114	-0.120	-0.105	-0.069	-0.066
	(0.078)	(0.078)	(0.077)	(0.077)	(0.076)	(0.075)	(0.072)	(0.073)
Unimproved roof material	0.000	-0.001	0.002	0.001	-0.007	0.009	0.094	0.095
	(0.088)	(0.087)	(0.088)	(0.087)	(0.089)	(0.087)	(0.088)	(0.086)
Unimproved wall material	-0.519***	-0.520***	-0.536***	-0.537***	-0.548***	-0.520***	-0.398***	-0.401***
	(0.152)	(0.148)	(0.146)	(0.142)	(0.145)	(0.133)	(0.138)	(0.134)
Unimproved floor material	0.012	0.008	-0.006	-0.009	0.002	-0.015	-0.033	-0.039
	(0.079)	(0.079)	(0.081)	(0.081)	(0.079)	(0.080)	(0.064)	(0.064)
Unimproved drinking water source	-0.625***	-0.629***	-0.556***	-0.561***	-0.558***	-0.570***	-0.582***	-0.588***
	(0.084)	(0.085)	(0.085)	(0.085)	(0.086)	(0.084)	(0.072)	(0.073)
Unimproved toilet facility	-0.057	-0.056	-0.078	-0.077	-0.085	-0.061	-0.068	-0.066
	(0.090)	(0.092)	(0.094)	(0.095)	(0.094)	(0.093)	(0.083)	(0.085)
Not collected solid waste	-0.154**	-0.166***	-0.139**	-0.152**	-0.132**	-0.148**	-0.132**	-0.147***
	(0.061)	(0.059)	(0.061)	(0.059)	(0.063)	(0.059)	(0.055)	(0.055)

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Table C.2 – *Continued from previous page*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Access to electricity	0.477***	0.481***	0.428***	0.433***	0.424***	0.446***	0.369***	0.374***
	(0.071)	(0.071)	(0.075)	(0.076)	(0.076)	(0.078)	(0.065)	(0.066)
Dwelling tenure agreement								
No Agreement							ref.	ref.
Written Agreement							0.142	0.116
							(0.091)	(0.087)
Non-written Agreement							0.021	0.010
							(0.068)	(0.067)
Not Applicable							0.000	0.000
							(.)	(.)
Dwelling tenure status								
Owner							ref.	ref.
Rented							-1.074***	-1.061***
							(0.124)	(0.124)
Free							0.000	0.000
							(.)	(.)
Other							0.685***	0.727***
							(0.110)	(0.112)
Urban district	0.234***	0.228***	0.120	0.115	0.115	0.122	0.085	0.081
	(0.084)	(0.080)	(0.090)	(0.086)	(0.090)	(0.086)	(0.090)	(0.091)
Affected by flood					0.513			
					(0.423)			
Affected by flood $\times$ Job density					-0.304			
					(0.209)			
Flood event is likely						-0.316		
						(0.193)		

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Table C.2 – *Continued from previous page*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Flood event is likely × Job density						0.132		
						(0.086)		
Observations	916	916	916	916	916	916	916	916
R2	0.47	0.47	0.48	0.48	0.48	0.48	0.60	0.60

Note: The dependent variable is the log of rent (combined rent paid and self-estimated rent), measured in 2017 PPP US$by year. Robust standard errors are clustered at the enumeration area level. The variable Dwelling tenure status it is not added because is collinear with tenure agreement, for the observations of Antananarivo. *** p<0.01, ** p<0.05, and * p<0.1.

TABLE C.3: Estimation of rent, DAR ES SALAAM

	Simple		Job density		Interaction		Tenure	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Directly affected by flood	0.077		0.084				0.086	
	(0.080)		(0.079)				(0.078)	
Flood risk perception		0.242***		0.251***				0.244***
		(0.091)		(0.091)				(0.092)
Job density			-0.070	-0.083	-0.120	-0.114	-0.064	-0.076
			(0.116)	(0.115)	(0.120)	(0.110)	(0.117)	(0.116)
Unimproved house	-0.111	-0.143*	-0.111	-0.144*	-0.119	-0.137	-0.116	-0.149*
	(0.081)	(0.085)	(0.080)	(0.085)	(0.080)	(0.085)	(0.081)	(0.085)
Unimproved roof material	-0.088	-0.086	-0.096	-0.096	-0.104	-0.119	-0.084	-0.087
	(0.163)	(0.154)	(0.163)	(0.153)	(0.163)	(0.152)	(0.163)	(0.153)
Unimproved wall material	0.124	0.111	0.126	0.114	0.124	0.113	0.132	0.120
	(0.085)	(0.090)	(0.087)	(0.092)	(0.087)	(0.091)	(0.086)	(0.092)
Unimproved floor material	-0.217*	-0.242*	-0.214*	-0.239*	-0.219*	-0.208*	-0.162	-0.196
	(0.117)	(0.132)	(0.119)	(0.136)	(0.120)	(0.126)	(0.124)	(0.142)
Unimproved drinking water source	-0.233**	-0.232**	-0.227**	-0.225**	-0.234**	-0.224**	-0.224**	-0.223**
	(0.101)	(0.098)	(0.098)	(0.095)	(0.098)	(0.095)	(0.099)	(0.096)
Unimproved toilet facility	-0.685***	-0.700***	-0.681***	-0.695***	-0.669***	-0.702***	-0.678***	-0.693***
	(0.114)	(0.113)	(0.112)	(0.111)	(0.112)	(0.110)	(0.113)	(0.112)
Not collected solid waste	-0.253**	-0.224**	-0.299**	-0.277**	-0.309**	-0.299**	-0.278**	-0.259**
	(0.098)	(0.093)	(0.123)	(0.119)	(0.124)	(0.116)	(0.128)	(0.125)
Electric lighting	0.496***	0.485***	0.495***	0.482***	0.504***	0.470***	0.479***	0.469***
	(0.084)	(0.080)	(0.086)	(0.081)	(0.088)	(0.082)	(0.086)	(0.082)
Dwelling tenure agreement								
No Agreement							ref.	ref.

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Table C.3 – *Continued from previous page*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Written Agreement							-0.303***	-0.358***
							(0.104)	(0.107)
Non-written Agreement							-0.440***	-0.470***
							(0.143)	(0.142)
Affected by flood					-0.562			
					(0.387)			
Affected by flood × Job density					0.315			
					(0.200)			
Flood event is likely						-0.383		
						(0.662)		
Flood event is likely × Job density						0.299		
						(0.316)		
Observations	466	466	466	466	466	466	466	466
R2	0.32	0.34	0.33	0.34	0.33	0.34	0.33	0.34

Note: The dependent variable is the log of rent (combined rent paid and self-estimated rent), measured in 2017 PPP US$by year. The variables *Number of rooms* and *Number of rooms squared* are added only in estimations (7) and (8) because of missing values reducing the total number of observations. The variable *Dwelling tenure status* is not added because all the observations for rent are only for renters. Robust standard errors are clustered at the enumeration area level. *** p<0.01, ** p<0.05, and * p<0.1.

TABLE C.4: Estimation of rent, ADDIS ABABA

	Simple		Job density		Interaction		Tenure	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Directly affected by flood	-1.054**		-0.863**				-0.822**	
	(0.391)		(0.361)				(0.335)	
Flood risk perception		-0.249		-0.269				-0.197
		(0.257)		(0.227)				(0.226)
Job density			-0.744***	-0.773***	-0.687**	-0.706**	-0.464**	-0.492**
			(0.250)	(0.255)	(0.284)	(0.304)	(0.192)	(0.196)
Number of rooms	1.044***	1.046***	0.919***	0.916***	0.919***	0.923***	0.813***	0.812***
	(0.205)	(0.214)	(0.140)	(0.146)	(0.138)	(0.145)	(0.142)	(0.140)
Number of rooms squared	-0.081***	-0.082***	-0.070***	-0.070***	-0.070***	-0.071***	-0.060***	-0.060***
	(0.018)	(0.019)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Unimproved house	-1.102***	-1.195***	-0.712**	-0.776***	-0.696**	-0.771***	-0.600**	-0.668**
	(0.326)	(0.350)	(0.263)	(0.273)	(0.260)	(0.267)	(0.270)	(0.280)
Unimproved roof material	0.002	0.092	0.030	0.120	0.081	0.135	0.066	0.141
	(0.236)	(0.253)	(0.231)	(0.260)	(0.249)	(0.264)	(0.200)	(0.229)
Unimproved floor material	-0.548*	-0.608**	-0.619**	-0.664**	-0.606**	-0.661**	-0.529*	-0.573*
	(0.268)	(0.283)	(0.267)	(0.277)	(0.267)	(0.276)	(0.282)	(0.294)
Unimproved drinking water source	0.938**	0.577	0.592	0.294	0.347	0.233	0.554	0.271
	(0.381)	(0.370)	(0.409)	(0.505)	(0.493)	(0.525)	(0.336)	(0.402)
Unimproved toilet facility	-0.555***	-0.618***	-0.511**	-0.558***	-0.527***	-0.564***	-0.409***	-0.463***
	(0.161)	(0.162)	(0.186)	(0.187)	(0.177)	(0.185)	(0.121)	(0.124)
Not collected solid waste	-0.361	-0.367	-0.287	-0.300	-0.305	-0.318	-0.493	-0.482
	(0.409)	(0.437)	(0.379)	(0.389)	(0.377)	(0.385)	(0.446)	(0.456)
Electric lighting	-1.153	-1.347	-0.497	-0.614	-0.567	-0.701	0.154	0.018
	(0.896)	(0.991)	(1.002)	(1.088)	(0.978)	(1.119)	(1.039)	(1.107)

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Table C.4 – *Continued from previous page*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dwelling tenure agreement								
No Agreement							ref.	ref.
Written Agreement							-0.789***	-0.720***
							(0.206)	(0.209)
Non-written Agreement							0.143	0.268
							(0.227)	(0.233)
Dwelling tenure status								
Owner							ref.	ref.
Rented							-1.049***	-1.049***
							(0.339)	(0.343)
Free							-0.120	-0.131
							(0.170)	(0.175)
Other							-0.598	-0.543
							(0.552)	(0.560)
Affected by flood					-0.054			
					(0.579)			
Affected by flood × Job density					-0.397			
					(0.372)			
Flood event is likely						0.060		
						(0.504)		
Flood event is likely × Job density						-0.195		
						(0.337)		
Observations	751	751	751	751	751	751	736	736
R2	0.36	0.35	0.43	0.42	0.43	0.42	0.49	0.48

Note: The dependent variable is the log of rent (combined rent paid and self-estimated rent), measured in 2017 PPP US$by year. Robust standard errors are clustered at the enumeration area level. *** p<0.01, ** p<0.05, and * p<0.1.

D Additional estimations and analysis

TABLE D.1: Descriptive statistics by city, total sample

	Accra		Antananarivo		Dar es Salaam		Addis Ababa	
	Obs	%	Obs	%	Obs	%	Obs	%
Exposure to floods								
Households directly affected by flood	1,006	44.6	2,272	8.1	1,335	22.3	810	7.9
Households that perceive flood risk as high	1,006	40.3	2,272	47.2	1,335	20.7	810	31.3
Dwelling tenure	1,006		2,272		1,335		795	
Owner	204	20.3	988	43.5	783	56.7	435	54.7
Rented	442	44.0	775	34.1	483	36.2	333	41.9
Free	296	29.4	382	16.8	64	4.8	21	2.7
Other	63	6.3	128	5.6	5	0.4	5	0.7
Housing conditions								
Access to improved toilet facility	1,006	15.6	2,272	5.2	1,335	31.3	810	28.7
Access to improved drinking water	1,006	45.3	2,272	18.7	1,335	42.7	810	98.2
Access to collected solid waste	1,006	74.0	2,272	59.2	1,335	83.9	810	66.6
Lighting with electricity	1,006	96.7	1,863	99.3	1,335	90.4	810	99.5
	Obs	Mean	Obs	Mean	Obs	Mean	Obs	Mean
Household size	1,006	3.4	2,272	4.2	1,335	4.1	810	4.3
Number of rooms	1,006	1.5	2,272	2.1	1,053	3.7	810	3.2
Job density	820	1.5	2,261	1.9	1,335	2.0	810	1.7

Notes: Figures are weighted.

TABLE D.2: Comparison of rent variables, ACCRA

	Rent value		Self estimated rent		Combined self estimated rent	
	(1)	(2)	(3)	(4)	(5)	(6)
Directly affected by flood	-0.024		-0.033		-0.198*	
	(0.100)		(0.048)		(0.112)	
Flood risk perception		-0.150		-0.052		-0.253**
		(0.139)		(0.060)		(0.106)
Job density	-0.264*	-0.257*	-0.285**	-0.278**	-0.814***	-0.789***
	(0.151)	(0.153)	(0.123)	(0.123)	(0.274)	(0.276)
Number of rooms	0.641***	0.600***	0.485***	0.480***	0.391***	0.369***
	(0.123)	(0.110)	(0.070)	(0.073)	(0.114)	(0.111)
Number of rooms squared	-0.108***	-0.099***	-0.047***	-0.047***	-0.048***	-0.045***
	(0.017)	(0.015)	(0.008)	(0.008)	(0.013)	(0.012)
Unimproved house	-0.461**	-0.458**	-0.313***	-0.312***	-0.310*	-0.302*
	(0.182)	(0.177)	(0.070)	(0.071)	(0.157)	(0.153)
Unimproved roof material	0.208***	0.206***	0.142***	0.141***	0.487***	0.481***
	(0.077)	(0.075)	(0.045)	(0.045)	(0.096)	(0.097)
Unimproved wall material	-0.200**	-0.203**	-0.259***	-0.258***	-0.337***	-0.337***
	(0.092)	(0.097)	(0.043)	(0.045)	(0.118)	(0.118)
Unimproved floor material	-0.037	-0.018	-0.102	-0.113	-0.044	-0.107
	(0.145)	(0.165)	(0.105)	(0.108)	(0.234)	(0.253)
Unimproved drinking water source	-0.051	-0.036	-0.071	-0.071	-0.076	-0.081
	(0.070)	(0.079)	(0.046)	(0.046)	(0.097)	(0.093)
Unimproved toilet facility	0.175	0.184	-0.248***	-0.248***	-0.078	-0.088
	(0.219)	(0.210)	(0.047)	(0.046)	(0.111)	(0.100)
Not collected solid waste	0.034	0.035	0.045	0.041	0.097	0.076
	(0.107)	(0.103)	(0.044)	(0.045)	(0.110)	(0.108)

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Table D.2 – *Continued from previous page*

	(1)	(2)	(3)	(4)	(5)	(6)
Electric lighting	-0.085	-0.134	0.262***	0.261***	0.581***	0.574***
	(0.119)	(0.140)	(0.064)	(0.064)	(0.172)	(0.185)
Observations	375	375	815	815	817	817
R2	0.11	0.12	0.38	0.38	0.19	0.20

Notes: The dependent variables are in log, measured in 2017 PPP US$by year. Robust standard errors are clustered at the enumeration area level. *** p<0.01, ** p<0.05, and * p<0.1.

TABLE D.3: Comparison of rent variables, ANTANANARIVO

	Rent value		Self estimated rent		Combined self estimated rent	
	(1)	(2)	(3)	(4)	(5)	(6)
Directly affected by flood	-0.156		-0.058		-0.140	
	(0.100)		(0.249)		(0.107)	
Flood risk perception		-0.067		-0.092		-0.044
		(0.062)		(0.233)		(0.064)
Job density	0.174***	0.171***	0.236	0.245*	0.164***	0.164***
	(0.057)	(0.056)	(0.148)	(0.147)	(0.057)	(0.057)
Number of rooms	0.567***	0.555***	0.505***	0.502***	0.640***	0.640***
	(0.107)	(0.106)	(0.169)	(0.166)	(0.052)	(0.052)
Number of rooms squared	-0.048**	-0.046**	-0.030**	-0.030**	-0.038***	-0.038***
	(0.021)	(0.021)	(0.012)	(0.011)	(0.007)	(0.006)
Unimproved house	-0.088	-0.082	-0.052	-0.044	-0.117	-0.114
	(0.064)	(0.065)	(0.193)	(0.203)	(0.077)	(0.077)
Unimproved roof material	0.110	0.116	0.075	0.078	0.002	0.001
	(0.102)	(0.100)	(0.174)	(0.171)	(0.088)	(0.087)
Unimproved wall material	-0.423***	-0.419***	-0.223	-0.262	-0.536***	-0.537***
	(0.149)	(0.144)	(0.418)	(0.391)	(0.146)	(0.142)
Unimproved floor material	-0.083	-0.087	0.160	0.143	-0.006	-0.009
	(0.062)	(0.063)	(0.245)	(0.239)	(0.081)	(0.081)
Unimproved drinking water source	-0.565***	-0.568***	-0.712***	-0.710***	-0.556***	-0.561***
	(0.079)	(0.079)	(0.199)	(0.202)	(0.085)	(0.085)
Unimproved toilet facility	-0.051	-0.044	-0.213	-0.218	-0.078	-0.077
	(0.094)	(0.097)	(0.239)	(0.231)	(0.094)	(0.095)
Not collected solid waste	-0.179***	-0.192***	0.116	0.120	-0.139**	-0.152**
	(0.054)	(0.052)	(0.228)	(0.243)	(0.061)	(0.059)

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Table D.3 – *Continued from previous page*

	(1)	(2)	(3)	(4)	(5)	(6)
Access to electricity	0.353***	0.362***	0.360	0.353	0.428***	0.433***
	(0.065)	(0.066)	(0.314)	(0.317)	(0.075)	(0.076)
Urban district	0.050	0.047	0.206	0.233	0.120	0.115
	(0.096)	(0.092)	(0.252)	(0.299)	(0.090)	(0.086)
Observations	784	784	132	132	916	916
R2	0.49	0.49	0.38	0.38	0.48	0.48

Notes: The dependent variables are in log, measured in 2017 PPP US$by year. Robust standard errors are clustered at the enumeration area level. *** $p<0.01$, ** $p<0.05$, and * $p<0.1$.

TABLE D.4: Comparison of rent variables, DAR ES SALAAM

	Rent value		Self estimated rent		Combined self estimated rent	
	(1)	(2)	(3)	(4)	(5)	(6)
Directly affected by flood	0.087		0.047		0.084	
	(0.079)		(0.081)		(0.079)	
Flood risk perception		0.240***		0.268***		0.251***
		(0.090)		(0.095)		(0.091)
Job density	-0.074	-0.085	0.072	0.054	-0.070	-0.083
	(0.116)	(0.115)	(0.111)	(0.110)	(0.116)	(0.115)
Unimproved house	-0.109	-0.140	-0.110	-0.147	-0.111	-0.144*
	(0.081)	(0.085)	(0.091)	(0.091)	(0.080)	(0.085)
Unimproved roof material	-0.102	-0.102	-0.323*	-0.320*	-0.096	-0.096
	(0.163)	(0.153)	(0.179)	(0.174)	(0.163)	(0.153)
Unimproved wall material	0.129	0.119	0.160*	0.140	0.126	0.114
	(0.087)	(0.091)	(0.090)	(0.099)	(0.087)	(0.092)
Unimproved floor material	-0.210*	-0.235*	-0.272**	-0.296**	-0.214*	-0.239*
	(0.120)	(0.136)	(0.131)	(0.146)	(0.119)	(0.136)
Unimproved drinking water source	-0.219**	-0.217**	-0.115	-0.112	-0.227**	-0.225**
	(0.096)	(0.094)	(0.108)	(0.105)	(0.098)	(0.095)
Unimproved toilet facility	-0.687***	-0.699***	-0.762***	-0.778***	-0.681***	-0.695***
	(0.112)	(0.111)	(0.115)	(0.113)	(0.112)	(0.111)
Not collected solid waste	-0.297**	-0.276**	-0.209	-0.192	-0.299**	-0.277**
	(0.123)	(0.119)	(0.129)	(0.124)	(0.123)	(0.119)
Electric lighting	0.493***	0.481***	0.403***	0.391***	0.495***	0.482***
	(0.086)	(0.082)	(0.126)	(0.119)	(0.086)	(0.081)
Observations	465	465	466	466	466	466

R2	0.33	0.34	0.29	0.31	0.33	0.34

Notes: The dependent variables are in log, measured in 2017 PPP US$by year. Robust standard errors are clustered at the enumeration area level. *** p<0.01, ** p<0.05, and * p<0.1.

TABLE D.5: Comparison of rent variables, ADDIS ABABA

	Rent value		Self estimated rent		Combined self estimated rent	
	(1)	(2)	(3)	(4)	(5)	(6)
Directly affected by flood	-0.260		-0.147		-0.863**	
	(0.694)		(0.239)		(0.361)	
Flood risk perception		0.017		-0.030		-0.273
		(0.529)		(0.109)		(0.226)
Job density	-1.476***	-1.501***	0.192***	0.189***	-0.744***	-0.778***
	(0.136)	(0.112)	(0.058)	(0.058)	(0.250)	(0.258)
Number of rooms	1.045**	1.056**	0.562***	0.561***	0.919***	0.907***
	(0.451)	(0.453)	(0.076)	(0.076)	(0.140)	(0.145)
Number of rooms squared	-0.117*	-0.118*	-0.039***	-0.039***	-0.070***	-0.069***
	(0.059)	(0.060)	(0.008)	(0.008)	(0.013)	(0.013)
Unimproved house	0.303	0.292	-0.281	-0.289	-0.712**	-0.766**
	(0.385)	(0.370)	(0.172)	(0.170)	(0.263)	(0.273)
Unimproved roof material	0.015	-0.003	0.162	0.176	0.030	0.124
	(0.708)	(0.671)	(0.174)	(0.177)	(0.231)	(0.257)
Unimproved floor material	-0.987	-1.030	-0.526***	-0.535***	-0.619**	-0.664**
	(0.637)	(0.675)	(0.138)	(0.135)	(0.267)	(0.278)
Unimproved drinking water source	-1.076	-1.294	0.275	0.223*	0.592	0.326
	(1.130)	(0.912)	(0.168)	(0.118)	(0.409)	(0.515)
Unimproved toilet facility	-1.291	-1.314	-0.259**	-0.267**	-0.511**	-0.558***
	(0.874)	(0.814)	(0.105)	(0.105)	(0.186)	(0.187)
Not collected solid waste	-0.716	-0.681	-0.251	-0.253	-0.287	-0.305
	(0.446)	(0.430)	(0.171)	(0.169)	(0.379)	(0.387)
Electric lighting	-0.055	-0.091	0.257	0.235	-0.497	
	(1.300)	(1.260)	(0.666)	(0.698)	(1.002)	

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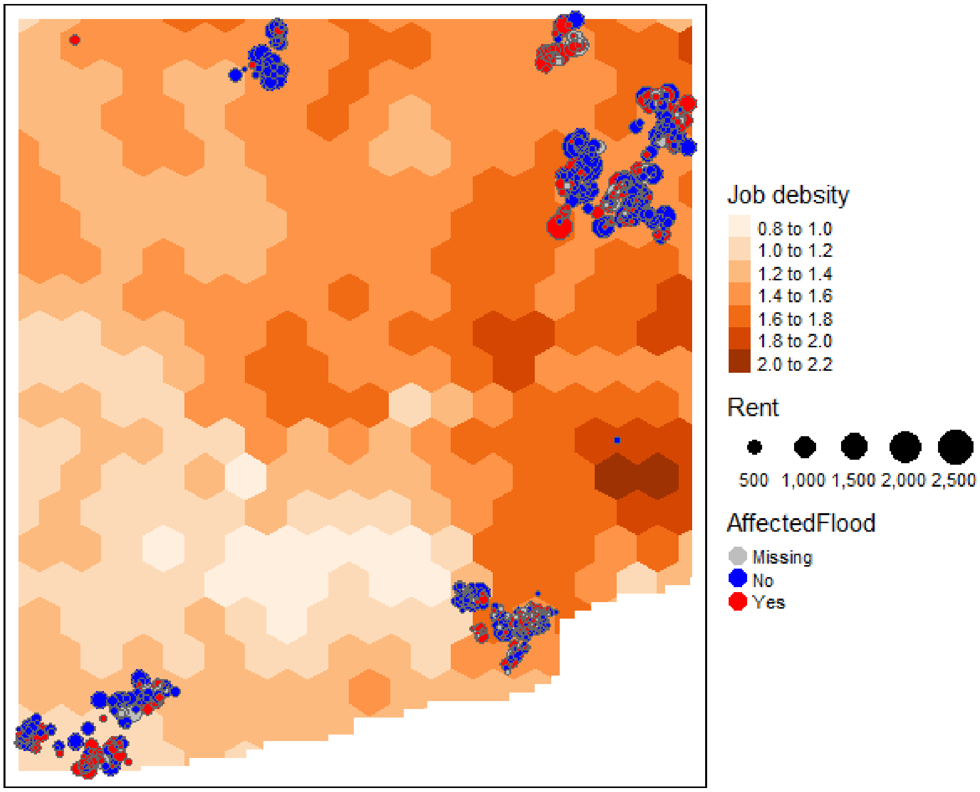
Table D.5 – *Continued from previous page*

	(1)	(2)	(3)	(4)	(5)	(6)
Observations	156	156	708	708	751	751
R2	0.42	0.41	0.47	0.47	0.43	0.42

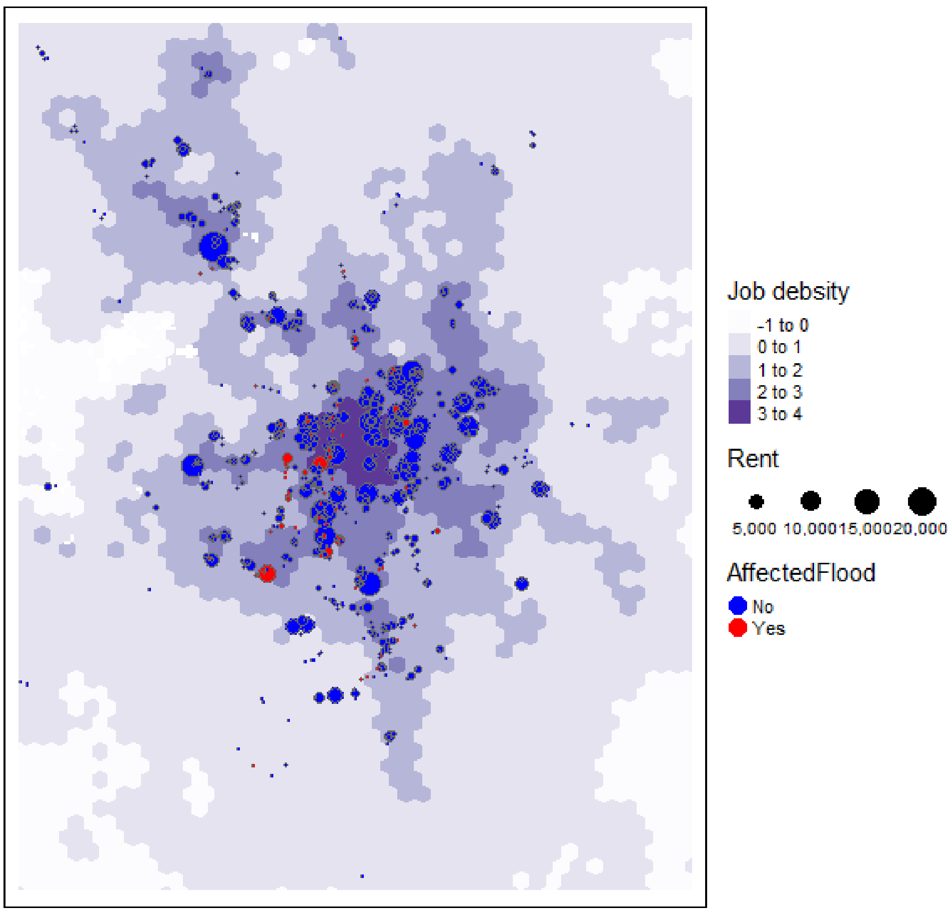
Notes: The dependent variables are in log, measured in 2017 PPP US$by year. Robust standard errors are clustered at the enumeration area level. *** p<0.01, ** p<0.05, and * p<0.1.

FIGURE D.1: Rent in surveyed households by exposure to floods, Accra



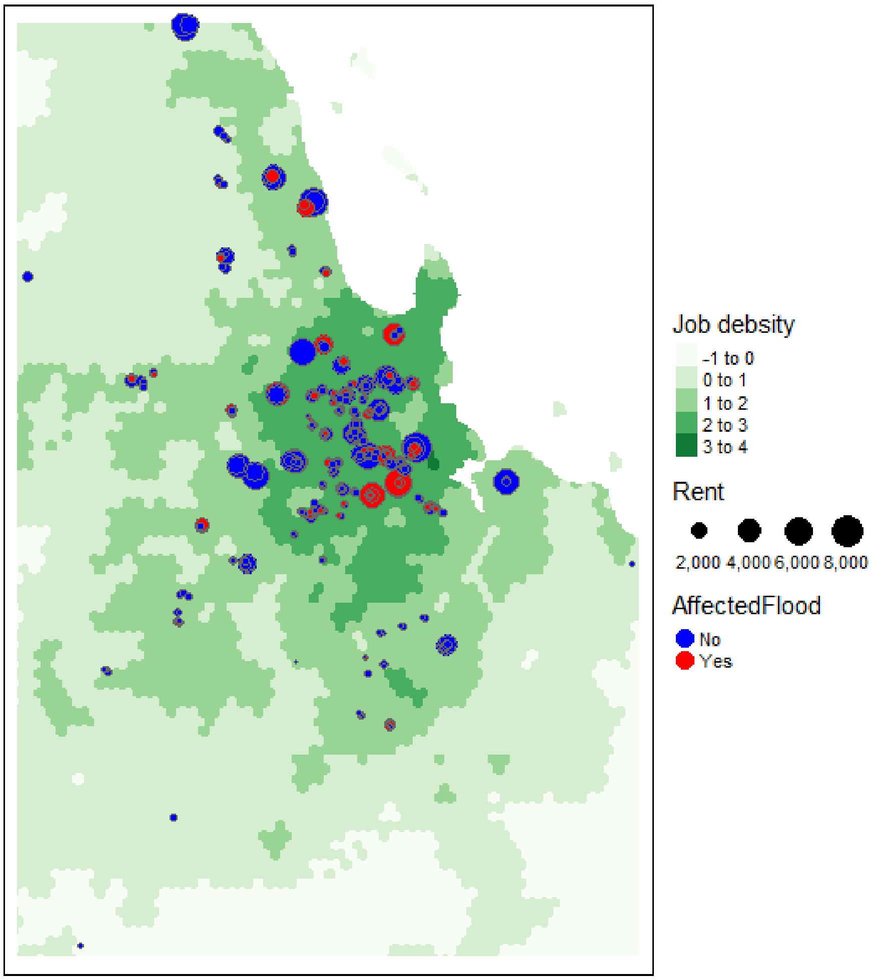
Source: Authors' calculation based on Disaster-Poverty Household Survey and Barzin et al. (2022) data.

FIGURE D.2: Rent in surveyed households by exposure to floods, Antananarivo



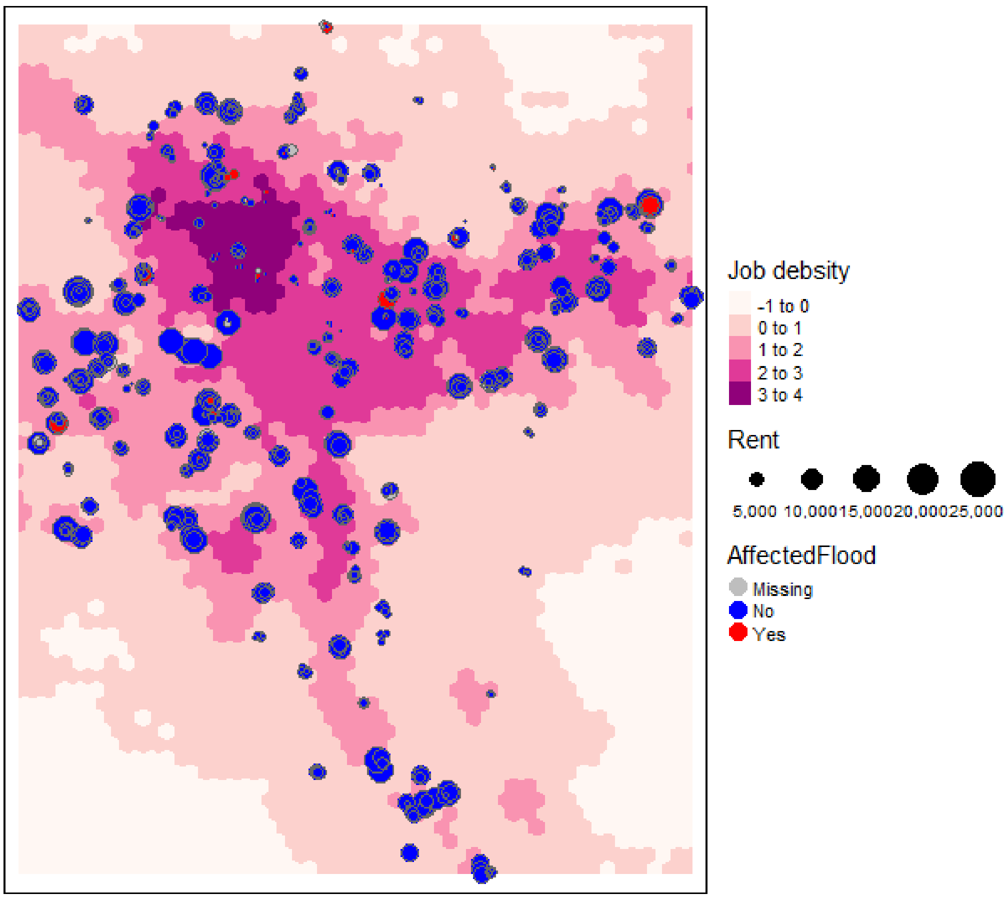
Source: Authors' calculation based on Disaster-Poverty Household Survey and Barzin et al. (2022) data.

FIGURE D.3: Rent in surveyed households by exposure to floods, Dar es Salaam



Source: Authors' calculation based on Disaster-Poverty Household Survey and Barzin et al. (2022) data.

FIGURE D.4: Rent in surveyed households by exposure to floods, Addis Ababa



Source: Authors' calculation based on Disaster-Poverty Household Survey and Barzin et al. (2022) data.