Transportation, Gentrification, and Urban Mobility: The Inequality Effects of Place-Based Policies *

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October 16, 2020

Preliminary version: please check with authors for most recent draft before circulating

Abstract

Roads, rail, and other public transport in a city are "place-based," in that they are built in specific neighborhoods. Do such investments benefit the poor? If people are mobile within a city, then any such place-based investment can lead to neighborhood changes, such as rent increases, which change who can afford to live near these investments and hence who benefits from them. We provide a tractable urban commuting model to study the distributional effects of urban infrastructure improvements. We derive intuitive "exact hat" expressions for the welfare change of initial residents after investment. We then apply the method to study the Dar es Salaam BRT system, using original panel data tracked on two dimensions (following households if they move and surveying all new residents of buildings). Preliminary results suggest that the BRT was a pro-poor investment: we estimate a welfare gain of 3.0% for incumbent low-income residents living near the BRT, compared with a 2.5% gain to incumbent high-income residents; across the city, poor gained on average 2.4% and rich gained 2.3%.

Keywords: Transport, Urbanization, Gentrification, Tanzania, House Prices
JEL Classification:

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*The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors. They do not necessarily represent the views of the World Bank and its affiliated organizations, or those of the Executive Directors of the World Bank or the governments they represent. We thank Jessica Mahoney, Juliana Aguilar, Justus Mugango, Rachel Steinacher, and Rachel Jones at IPA Tanzania for coordinating our data collection efforts in Tanzania. We also thank EDI for assistance with initial fieldwork. We thank Yonas Mchomvu at the World Bank and Ronald Lwakatare at the Dar es Salaam Rapid Transit Agency for institutional support. The research has been funded with UK aid from the UK government through the DIME ieConnect for Impact program at the World Bank. Additional funding is gratefully acknowledged from IGC, 3ie, and Stanford. Devika Lakhote, Caylee O'Connor, and Betsenat Gebrewold provided excellent research assistance. Any errors are our own.

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1 Introduction

It is currently estimated that developing world cities will need to accommodate over two billion more residents before 2050 (United Nations, 2018). This increase in the number of people living in dense urban areas has the potential to vastly increase productivity, but realizing these gains requires the provision of a large number of public goods, which become relatively more important as density rises. A significant portion of these public goods will be "place-based" in the sense that they are provided to a place and not to a set of people. This set of services include transport links, like light rail, that are tied to a physical location, school buildings, public parks, and sanitation infrastructure.

The place-based nature of these services raises an important challenge. Because people are relatively mobile within cities, any significant improvement in a location's amenity that comes from a piece of place-based infrastructure can essentially be purchased by those with enough money to afford the higher rents that likely accompany improved amenity. This leads to the possibility of gentrification, whereby neighborhood change characterized by improved amenities and rent increases may result in lower-income incumbent residents being displaced by higher-income in-movers (Kennedy and Leonard, 2001). Ensuring that the poor benefit from these policies is difficult, and it is even possible that a limited increase in the availability of these types of services can make poor renters worse off.

The potential for such effects has prompted widespread concern about the potential unintended consequences of infrastructure improvements and urban regeneration more broadly in developing country cities among both policymakers (Amirtahmasebi et al., 2016; UN-Habitat, 2012) and the public. Such concerns often center on poor renters who are a group that may be especially vulnerable to the effects of gentrification if they are unable to afford rental increases and do not enjoy the benefits of property price appreciation (Mayo and Angel, 1993; Martin and Beck, 2018; Kennedy and Leonard, 2001). Examination of the channels via which gentrification may affect this group is important for ensuring that program design and targeting minimize such adverse consequences and overcome potential political economy constraints to the implementation of projects.

We study these issues by investigating the likely impact of Dar es Salaam's bus rapid transport (BRT) system. With a growth rate of 6.5%, Dar es Salaam is one of the fastest-growing cities in Africa (The World Bank, 2019). Congestion is a severe problem (Mpogole and Msangi, 2016), which costs the city an estimated $1.8 million each day in lost productivity (The World Bank, 2019). To help address these challenges, the Tanzanian government is building a six-phase BRT system of dedicated trunk lanes spanning 141km. Operations commenced on the system's first phase, connecting the city's central business district to residential areas in the city's Northwest, in May 2016. Within its first year of operations, the system was carrying 165,000 passengers per day.

In this setting, our investigation draws on panel data that we have been collecting on a sample of around 1700 households since prior to the opening of the first line, and a quantitative model that is a simple extension of a canonical commuting model (similar to Ahlfeldt et al. (2016)). The existing model accommodates (endogenous) location-specific productivities and amenities and rents, and to this, we add non-homothetic preferences, exogenous type-specific productivities, and endogenous type-specific amenities. Despite these additional components we show that the model can be easily quantified with a sparse set of data. Applying the exact-hat methods popularized by Dekle et al. (2008) we show that average welfare gains by type can be recovered if a researcher knows three key ex-ante facts: i) the ex-ante living and working matrix by type, ii) the ex-ante expenditure on rent by location and type, iii) ex-ante earnings in each location broken down by type and living location; and four key parameters: i) an amenity or productivity sorting parameter, ii) the proportion of income spent on rent by type, iii) the elasticity of living location to rent by type, and iv) the proportion of production income paid to land. We next show that it is possible to derive average welfare gains by *initial* location and type using the same data and with knowledge of the parameter values. This "exact hat for gentrification" thus allows a direct quantification of urban investment projects' distributional effects. This derivation account for the fact that people initially choose where to live based on unobserved heterogeneity, such as preferences or productivities, and so the distribution of individuals living in a specific location is not a random draw of the population.

Having outlined the model and data, we then establish the model's suitability for our investigation and setting. In a series of simulations, we show that the model, while simple, accommodates a wide range of possible distributional impacts from building a BRT. Concentrating on the case with two types ("rich and poor") we show there are three possible gentrification outcomes possible. First, the inflow of new residents to a neighborhood can be balanced between rich and poor ("no gentrification"). Second, the rich can flow into a neighborhood proportionally more than the poor, but not push out (in an absolute sense) the poor already resident in the neighborhood ("weak gentrification). Third, the rich can move into a neighborhood and push out the poor residents already living there ("strong gentrification"); depending on the strength of the compensating general equilibrium forces and where the poor are displaced to, the displaced residents can either face a net welfare gain ("compensated strong gentrification") or face a net welfare loss ("uncompensated strong gentrification"). We then show that the model is consistent with several stylized facts from our data: a gravity commuting relationship holds in the data, weak evidence that the poor spend a larger proportion of their income on rent than do the rich, and the living location choices of the poor are more responsive to rents than are those of the rich. The key to the final result is that a BRT connection to a current low-income neighborhood can result in large rent increases, which displace poor people to formerly wealthy neighborhoods, which have poor access to the locations that the poor value both for amenity or productivity reasons.

Having established the flexibility of the model and its suitability to our setting, we then estimate the likely impact of the various Dar es Salaam BRT lines. We first show how to identify each of the key parameters discussed above. One of the model's key features is that a "gravity wage" equation (which holds at the population, not type, level) can be used to estimate the key sorting parameter that determines the productivity benefit of having workers who have higher skills accessing job locations. With these parameters in hand, we then produce estimates of the likely effects of the BRT lines. Our results indicate that there are not sizeable general equilibrium effects. As a consequence the aggregate welfare effects are primarily determined by the proportion of rich and poor types that, ex-ante, travel along the proposed BRT routes. Given this, the first BRT line, which runs mostly from a relatively wealthy neighborhood to downtown has a larger welfare gain for rich than poor. Line two mostly favors the poor, and in total, with all six lines built, we predict relatively equal welfare effects. Why are the welfare effects so similar for high and low types? This result comes from a combination of observations in the data. First, the ex-ante distribution of people across space indicates that there are not parts of Dar es Salaam that are particularly preferred by high or by low types. This then implies that "displacement" is not particularly costly. Second, while there are differences in expenditure on rents across types, this difference is more than enough to explain the difference across types in elasticity of living location to rental rates. Given this, we conclude that there are no strong externalities, so an influx of high types into an area does not strongly dissuade the poor from living there. Finally, for reasonable values of the importance of human capital in production, the small changes in commute choices predicted are insufficient to have large effects on the productivities of different locations. In interpreting these results it is important to note that the model, as discussed above, is quite capable of delivering a "gentrification effect" where the poor benefit much less than the rich; it is the data the suggests that this is not a likely outcome in the city of Dar es Salaam.

The paper contributes directly to the literature on spatial urban models (e.g., Ahlfeldt et al. (2016); Tsivanidis (2017)) and, more generally, to the literature on quantitative models of economic geography as recently surveyed by Redding and Rossi-Hansberg (2017). Most closely related is the work of Tsivanidis (2017), who studies the aggregate and inequality effects of the Bogota Transmilenio (also a BRT system).[1] Tsivanidis (2017) specifies a different form of non-homothetic preferences and uses impressive cross-sectional census-block data to identify all the key parameters in his model. We instead provide a non-homothetic model that preserves the ability to use exact-hat methods that require less data and provide a somewhat closer link between results and data. We also undertook original data collection to collect a *panel* of households and structures so can directly observe those displaced in the city. The methods are complementary, and like Tsivanidis (2017) we do not estimate very strong inequality effects.

[1]Other studies of BRT systems in particular include Bocarejo et al. (2013); Cervero and Kang (2011); Heres et al. (2014); Rodriguez and Targa (2004); Pfutze et al. (2018); Majid et al. (2018); Gaduh et al. (2020).

The remainder of the paper is structured as follows. Section 2 describes our data, Section 3 lays out the set of simple facts that motivate concerns about unequal effects of infrastructure and our particular modeling assumptions, Section 4 lays out the model and how it can be estimated with a minimum of data by applying exact-hat methods, Section 5 shows through simulations the flexibility of the model in producing a range of inequality effects and Section 6 estimates the key parameters in the model. Section 7 provides the main results while Section 8 offers some conclusions and ideas for future work.

2 Data

This section discusses the data we collected in Dar es Salaam. We collected a panel dataset over two dimensions. We enrolled households who live inside structures at baseline. We resurveyed the household members wherever they were living at endline (creating a panel of households), and we surveyed any new households residing in the original structures (creating a panel of structures).

2.1 Baseline household survey

A baseline household survey was conducted in February 2016, before the first phase of the BRT began operations in April. We used a geographical sampling strategy to ensure coverage across the entire city of Dar es Salaam by selecting 141 clusters at equal intervals along 12 arcs at radii increasing at 1.5km intervals from the central business district, as shown in Appendix Figure A1. We conducted interviews at 125 of these clusters.[2] At each cluster location, a random walk was used to select 12-14 households to interview, yielding a total of 1748 households that were available for and consented to interviews.

We conducted three interviews at each household. A household module was conducted with any knowledgeable household member found at the house, covering household demographics, dwelling information, assets, consumption, and summary education and employment information for all household members. A separate survey was then

[2]The remaining 16 clusters were military or special residence compounds, non-residential areas, or designated hazardous areas where we were not able to conduct interviews.

administered to one male and one female respondent aged above 17 years, randomly selected from their respective qualifying group in the household. This survey included more detailed questions on employment, income, commuting and neighborhood amenities. This survey was administered to a total of 3104 individuals.

2.2 Endline household survey

An endline household survey was conducted from February-May 2019.[3] All baseline respondents and structures were tracked as part of this survey. Hence, if a baseline household had moved out of its baseline structure, the household was tracked to its new structure, and interviews were conducted with both the original household in its new structure and with the new occupants of their original structure.[4] Baseline respondents who split from their baseline household and moved elsewhere were also tracked and a household survey conducted for their new household.

Table 1 summarizes structure-, household- and individual-level recontact rates at endline.[5] Surveying households in a dynamic urban setting is challenging. We successfully located 91.8% of our baseline structures at the endline approximately three years later and successfully surveyed 76% of the sample. 10% of households living in structures refused (either at the midline survey or at endline), 8.2% were not found (either at midline or at endline), and 5.8% of structures were torn down or empty. The second panel shows the contact rates for households. Overall, we made contact with 89.8% of the baseline sample, successfully surveying 79.6% of them at the endline. The individual contact rate was 84.9%; we successfully surveyed 69.7% of the original individual sample at endline. For the sample of households who were successfully surveyed during the midline, Column (2) shows that we resurveyed 88% of structures, 92% of households, and 81% of individuals at endline. We present balance tests for attrition across the three samples in Appendix Tables A2-A4. We do not find the geography (i.e., distance to the BRT) predicts who was

[3]We conducted a follow-up telephone survey in September-October 2019 to refine some variables given inconsistencies in some survey responses. Refer to the Data Appendix for full details.

[4]The only exception to this was households who had moved out of Dar es Salaam, who were not tracked.

[5]Appendix Table 1 shows the same table for ever-enrolled households. Midline and SMS surveys conducted in 2017-2018 were also conducted to keep in contact with as many respondents as possible between the baseline and endline surveys to reduce attrition.

successfully surveyed, but, as perhaps expected in locations with a large amount of mobility, we are more likely to be able to recontact individuals who were owners rather than renters, and those who had lived in their structure for more years.[6]

Table 1: Status of baseline sample at endline

	(1) Enrolled at baseline	(2) Still in sample at endline
Structures		
Found and survey complete	76.0	87.5
Found and refused /incomplete	10.0	3.6
Not found	8.2	2.1
Torn down / empty	5.8	6.7
N	1748	1517
Households		
Found and survey complete	79.6	92.2
Found and refused/incomplete	9.2	2.3
Not found	11.2	5.6
N	1748	1510
Male/female respondents		
Found and survey complete	69.7	81.3
Found and refused /incomplete	13.3	6.0
Not found	15.1	10.6
Died	1.8	2.1
N	3104	2662

Notes: Table shows percent in each status. We initially enrolled 1748 structures and households. Up to two individual respondents (one male, one female) were enrolled per household. We stopped tracking structures after midline if they (i) refused, or (ii) we were not able to locate either the structure or the household after exhausting all contact information available. We did not attempt to find non-tracked sample at endline.

2.3 Travel time data

A baseline travel time survey was conducted in January 2016. Enumerators traveled between six points on the periphery of Dar es Salaam and the central business district by daladala (minibus), taxi, motorbike, and bajaji (rickshaw), recording GPS locations and

[6]We consider bounds throughout the paper to account for the potential effects of the endogenous recontact rate.

time stamps along each journey route. A total of 812 trips were completed, spanning different days of the week and times of the day. These data were used to calculate average baseline travel speeds by car and public transport, where the latter averaged speeds across daladala and bajaji travel.

At the endline, GoogleMaps was used to estimate the average travel speed by car along the same routes as traversed by the enumerators in taxi/ private vehicles in the baseline travel time survey. This was obtained using GoogleMaps's preferred route's estimated travel speed in both directions between the six points used in the baseline travel time survey and the central business district, averaged across estimated travel speeds at 9 am, 12 noon and 5 pm. Average travel speeds by public transport at the endline were estimated by applying the car to public transport travel speed ratio from baseline, given GoogleMaps's coverage of public transport travel times did not extend to Dar es Salaam at the time of the endline survey.

Recorded departure and arrival times at all stops along the operational BRT route from February - May 2019 were obtained from DART and combined with distance data to yield average endline travel speeds along operational BRT routes.

Geocoded data on the entire road network in Dar es Salaam were obtained from OpenStreetMap at the time of the baseline and endline surveys.[7]

Baseline and endline travel times between spatial units used in our analysis were calculated using ArcGIS's Network Analyst extension (based on the Dijkstra algorithm). Travel times along the road network at baseline and endline were calculated using this tool, where travel speeds along the network were assigned to be (i) the average baseline public transport travel speed at baseline, (ii) the average BRT travel speed for roads along the operational BRT route at endline, (ii) the average endline public transport travel speed along all other roads at endline.

[7]A comparison of these maps reveals enormous changes in the network, which are likely attributable to increasing coverage of OpenStreetMap maps rather than new road construction. As such, the 2019 map is used in all travel time calculations. We present results showing the robustness of our results to instead using the 2015 map for 2015 travel time calculations.

2.4 Population data

Population data for enumeration areas in Dar es Salaam were obtained from the country's most recent population census, the 2012 Population and Housing Census. This gives aggregated total population counts by sex for each enumeration area. Appendix Figure A2 plots the census plot for each of the surveyed wards. The surveyed area covers 87% of the population of Dar es Salaam.

2.5 Empirical context: BRT in Dar es Salaam

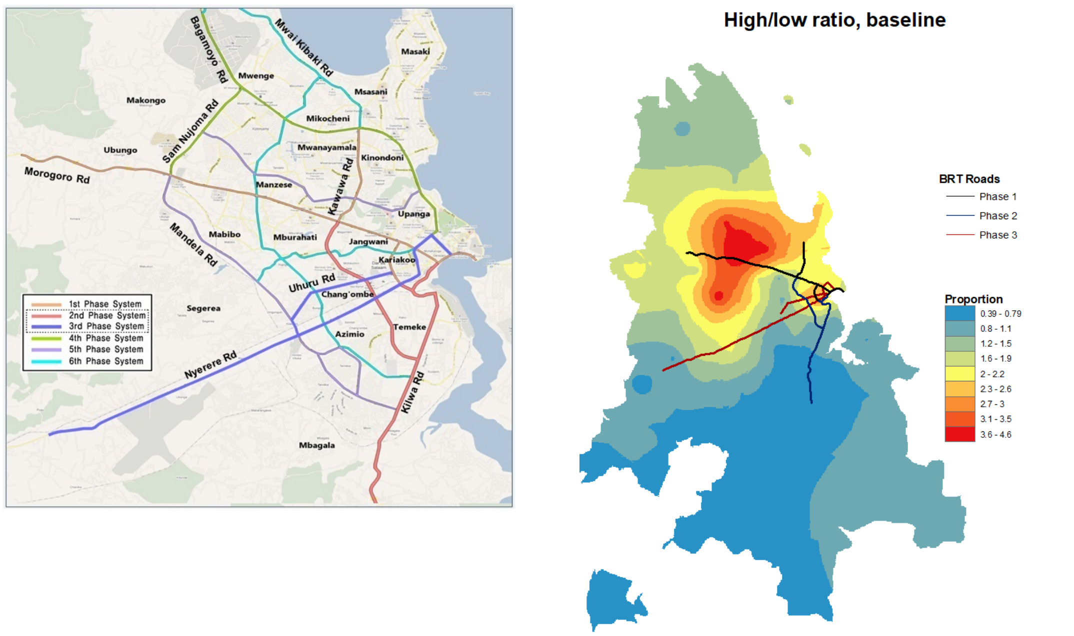
With a growth rate of 6.5%, Dar es Salaam is one of the fastest-growing cities in Africa (The World Bank (2019)). Congestion is a severe problem (Mpogole and Msangi (2016)), which costs the city an estimated $1.8 million each day in lost productivity (The World Bank (2019)). To help address these challenges, a six-phase BRT system of dedicated trunk lanes spanning 141km, shown in Figure 1, is being implemented in the city from 2005-2035. Operations commenced on the system's first phase, connecting the city's central business district to residential areas in the city's northwest (Kinondoni), in May 2016. Within its first year of operations, the system was carrying 165,000 passengers per day. Later phases of the BRT system are planned along other radial routes connecting the central business district to the south (Temeke district, Phase 2), southwest (Ilala district, Phase 3), and north (Phase 4), as well as orbital and connecting routes (Phases 5 and 6).

2.6 Defining low and high types

The analysis focuses on the gentrification effects of place-based policies that may have adverse consequences for poor incumbent residents. We define households based on consumption per adult equivalent member. We consider four alternative measures of poverty: Tanzania's national poverty line of 49,320 TZS per day; the World Bank's extreme poverty line of USD 1.90 per day; and two higher World Bank poverty lines: a $3.20 international poverty line and an upper middle-income international poverty line of $5.50 per day. Table 2 shows the share of our sample who are classified as nonpoor under each definition. The national poverty line is very close to the World Bank's extreme

Figure 1: BRT locations and initial distribution of high/low

(a) BRT system map (b) Initial distribution of poor and rich



poverty line. By that measure, 3.8% of the sample is poor. 87% of households have the same poverty classification in the EL survey as the BL survey. The poverty rate under the \$3.20 per day poverty line is 19.9%, and the poverty rate under the \$5.50 per day poverty line is 55%. In what follows, we use the \$5.50 per day measure to classify households into "low" and "high" income as it splits households into two approximately equal-sized groups.[8]

The distribution of high and low types by this definition across the city at baseline is not uniform. Panel (b) of Figure 1 plots the relative distribution of high to low-income households across the city at baseline. The first phase of the BRT connects the relatively affluent neighborhood of Kinondoni to the CBD. In comparison, Phase 2, which connects Temeke to the CBD, has a much lower proportion of high-income residents, and Ilala, which is the site for Phase 3, an intermediate amount.

[8] We assign individuals to be 'low' or 'high' type based on their baseline characteristics, and for those who enter the sample at endline, assign their type based on their endline characteristics. We present robustness of the results to instead assigning individuals' type based on their characteristics in each period.

Table 2: Share of nonpoor (high) households

	(1) Mean	(2) Share of BL with same type in EL
Above TZ poverty line	0.962	0.868
Above WB USD 1.90 poverty line	0.962	0.867
Above WB USD 3.20 poverty line	0.801	0.709
Above WB USD 5.50 poverty line	0.446	0.649
N	1721	1475

Notes: Table shows stability of different measures of high type. Asset is computed by above/below median of hh asset index. BPL uses TZ national poverty line. The USD 1.90 is the WB's poverty line (in 2011) for extreme poverty and the USD 3.20 is the WB poverty line for lower middle-income poverty. A stable HH is one where both male/female respondents remain in the hh at endline. A split household is one where one respondent has left the hh and been assigned a new hh ID.

3 Motivating Facts

We start by asking who uses the BRT, whether the BRT changed the price of housing, and whether the composition of people near the BRT changed. To do so, we compare outcomes for households living within a 2km radius of Phase 1 with those living within 2 km of Phase 3, which we use a placebo line. [9]

3.1 BRT usage and impact on travel times

The BRT is widely used. At endline, 31% of respondents (52% of those living within two kilometers of Phase 1) had used the BRT within the last seven days, as shown in Table 3. Of those living near Phase 1, 35% report using the BRT to travel to a large public market (Kariakoo) connected by the line, and 12% report using the BRT to travel to work (conditional on working). High type individuals living close to the BRT are more likely to have used the BRT in the last seven days (58% versus 47% among low type individuals) and

[9] The BRT network has several intersecting routes. As a result, there is often a mechanical correlation between travel time change along Phase 1 and many of the later phases. Appendix Table A8 shows these correlations. We choose Phase 3 as a counterfactual as the change in travel time is negatively correlated with the change in travel time along Phase 1 as expected when the routes traverse difference parts of the city.

to use the BRT to commute to work, while a slightly higher share of low type individuals use the BRT to travel to markets. The higher usage among high type individuals is more pronounced in the full sample given the higher share of high types living closer to Phase 1.

Table 3: BRT usage stats (type defined by WB 5.50 poverty line hybrid)

	Whole sample	$<$ 2 km from Ph1
Whole sample		
Take BRT to Kariakoo	0.14	0.35
BRT main transport to work (if work)	0.04	0.10
BRT used in commute to work (if work)	0.07	0.12
Used BRT in last 7 days	0.31	0.52
Low		
Take BRT to Kariakoo	0.12	0.36
BRT main transport to work (if work)	0.03	0.08
BRT used in commute to work (if work)	0.07	0.11
Used BRT in last 7 days	0.26	0.47
High		
Take BRT to Kariakoo	0.17	0.32
BRT main transport to work (if work)	0.06	0.12
BRT used in commute to work (if work)	0.08	0.14
Used BRT in last 7 days	0.38	0.58

Notes: High type is hybrid above WB 5.50 poverty line based on expenditure (incl. imputed rent) per capita. Table gives mean of proportion of individuals who report using the BRT. Data from endline survey. Data weighted by computed survey weight.

We next present evidence that the BRT reduced travel times along the route. To do this, we use survey data collected at baseline and endline on the time for households to travel to Kariakoo market (located in downtown Dar on the Phase 1 BRT line) and ask how closely the change in reported travel time correlates with an instrument for travel time that predicts the time to each location with and without the BRT. We run the following regression:

$$\log \text{actual travel time}_{lt} = \beta \log \text{Instrument for travel time: Phase 1 BRT}_{lt} + \gamma_l + \gamma_t + \epsilon_{lt}$$

Table 4 shows that travel times to central markets reported in the survey data fell very close to one-for-one with the predicted travel time incorporating Phase 1 of the BRT: the elasticity (β) is 1.2. One concern with this finding is that there may have been improvements to travel speeds along arterial roads in the city more broadly over this period. These trends - rather than the BRT - may have driven the reported improvements in travel times. We investigate this using a placebo test based on Phase 3 of the BRT, which has not yet opened but is planned to run along a different arterial route in the city. As shown in Columns (2) Table 4, predicted travel times incorporating Phase 3 do not predict changes in reported travel times, alleviating concerns about travel time trends along arterial roads explaining the estimated elasticity.

Table 4: Reported survey travel time to CBD

Dep var: log travel time	(1) Phase 1 (Actual)	(2) Phase 3 (Placebo)
Instrument for traveltime: Ph. 1 BRT	1.203	
	0.516**	
Instrument for traveltime: Ph. 3 BRT		0.081
		0.623
Dum post	-0.456	-0.526
	0.067***	0.077***
N	102	102
LocFE	✓	✓

Notes: Traveltime using bl road speed. Standard errors clustered at the ward (n=52) level.

3.2 Effect of BRT on rental rates and share of high types

Were these improvements in travel times capitalized in local rental rate increases? To investigate this, we run the following difference-in-difference specifications at the structure s level, where l is the location the structure is located in and t is the time period:

$$\log y_{slt} = \beta_1 \text{close to Phase } 1_l + \beta_2 \text{Post}_t + \beta_3 \text{close to Phase } 1_t \times \text{Post}_t + \epsilon_{slt}$$

Starting with rent, Columns (1)-(4) of Table 5 suggest that between our baseline and endline surveys, rental rates rose more for structures within 2km of the Phase 1 BRT line relative to those the same distance from Phase 3.[10] The increase in rents raises the possibility of poor households being pushed out of the neighborhood because of rising rents. However, Columns (5) and (6) of Table 5 suggest that the share of high types fell, not rose.[11]This suggests that the local rental rate increases documented above did not displace lower-income incumbent residents. Column (7) and (8) indicate that the overall churn in buildings near Phase 1 was no higher than Phase 3.[12]

Table 5: did table: paper (type defined by WB 5.50 poverty line hybrid)

	Log expected rent prrm		Log residualized expected rent prrm		High types		Live in house < 3 yrs	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	-0.267	-0.236	-0.395	-0.383	0.014	0.060	0.171	0.032
	0.108**	0.158	0.086***	0.149**	0.047	0.026**	0.051***	0.052
$<$ 2 km from Ph 1	0.103		-0.018		0.257		-0.043	
	0.122		0.094		0.097**		0.065	
Post $\times$ $<$ 2 km from Ph 1	0.356	0.350	0.408	0.357	-0.061	-0.053	0.010	0.012
	0.160**	0.206	0.157**	0.199*	0.064	0.028*	0.066	0.068
N	723	518	723	518	801	666	838	730
structID		✓		✓		✓		✓
wgt	✓	✓	✓	✓	✓	✓	✓	✓

Notes: High type is hybrid above WB 5.50 poverty line based on expenditure (incl. imputed rent) per capita. Unit of observation is a structure by year. Sample is structures within 2 km of either Phase 1 or Phase 3. Standard errors clustered by ward (n=52).

We explore this result – that although the rent increased, the share of high types decreased – by running a regression that compares the increase in rent for high households relative to low households.[13] Columns (1)-(4) of Table 6 show that while rents increased

[10]We confirm that pretrends are not driving this result in Appendix Table A6, which uses pre-period data from the World Bank's Measuring Living Standards in Cities survey to demonstrate that these trends were not evident in the 18 months prior to the opening of the BRT Phase 1 line. Different households were surveyed in the Measuring Living Standards in Cities survey relative to our survey, so the specifications in Appendix Table A6 include only spatial unit fixed effects and use household by year rather than structure by year as the unit of observation.

[11]Appendix Table A7 also confirms the absence of pre-trends in this specification.

[12]The same patterns are present if we assign individuals' types based on their characteristics in each period (rather than their baseline characteristics for all but those who enter the sample at endline). We show these results in in Appendix Tables A9 and A10.

[13]i.e., A triple difference regression with:

$$\begin{aligned}\log y_{slt} &= \beta_1 \text{close to Phase } 1_l + \beta_2 \text{Post}_t + \beta_3 \text{High type} + \beta_4 \text{close to Phase } 1_l \times \text{Post}_t \\ &+ \beta_5 \text{close to Phase } 1_l \times \text{High type} + \beta_6 \text{Post}_t \times \text{High type} + \beta_7 \text{close to Phase } 1_l \times \text{Post}_t \times \text{High type} + \epsilon_{slt}\end{aligned}$$

more for structures closer to Phase 1 after the BRT, this effect was particularly pronounced for the rents for high-income households near the BRT, with the estimated coefficient on the triple interaction is between 0.48-0.58, although the differential effect is not statistically significant across all specifications. This large increase in rent for high types is also associated with higher turnover for high types living near the BRT: Columns (5) and (6) show that high types were 15-27% more likely to have moved house compared with low types after the introduction of the BRT.

Table 6: triplediff table: paper (type defined by WB 5.50 poverty line hybrid)

	Log expected rent prrm		Log residualized expected rent prrm		Live in house $<$ 3 yrs	
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.183	-0.179	-0.316	-0.340	0.047	-0.166
	0.122	0.174	0.074***	0.144**	0.043	0.053***
$<$ 2 km from Ph 1	0.052		-0.009		-0.116	
	0.098		0.069		0.069	
Post $\times$ $<$ 2 km from Ph 1	0.169	0.153	0.232	0.149	0.092	0.090
	0.182	0.233	0.134*	0.194	0.076	0.077
High type	0.428	0.850	0.319	0.833	-0.222	1.015
	0.119***	0.474*	0.102***	0.513	0.079***	0.074***
Post $\times$ High type	-0.276	-0.297	-0.254	-0.261	0.175	0.151
	0.202	0.274	0.146*	0.233	0.107	0.101
$<$ 2 km from Ph 1 $\times$ High type	-0.096	-0.773	-0.152	-1.041	0.237	-1.182
	0.152	0.538	0.176	0.559*	0.096**	0.186***
Post $\times$ $<$ 2 km from Ph 1 $\times$ High type	0.530	0.563	0.475	0.579	-0.270	-0.151
	0.340	0.349	0.326	0.314*	0.132*	0.125
N	712	504	712	504	801	666
structID		✓		✓		✓
wgt	✓	✓	✓	✓	✓	✓

Notes: High type is hybrid above WB 5.50 poverty line based on expenditure (incl. imputed rent) per capita. Unit of observation is a structure by year. Sample is structures within 2 km of either Phase 1 or Phase 3. Standard errors clustered by ward (n=52).

Taking stock, we show that the BRT is widely used, especially by high types, and led to improvements in travel times to destinations along the Phase 1 route. The BRT led to differential rent increases near the new infrastructure. These factors suggest that concerns about gentrification may be pertinent in this setting. However, the motivating evidence also indicates that these rental rate increases may have affected high types most acutely. The share of high types living nearby decreased close to the Phase 1 BRT route relative to areas close to Phase 3. These patterns suggest a complex interaction between the housing market and an individual's preferences for where to live. Next, we turn to a structural spatial model to investigate the mechanisms via which the economy adjusted to the BRT's arrival and the potential importance of different channels of gentrification and degentrification.

4 Model

This section presents a model that can be used to analyze whether a particular piece of infrastructure leads to gentrification or degentrification. We first outline a stripped-down model in which all prices are taken as exogenous, and in which there are two types of people, low types ($t = L$) who have on average lower incomes, and high types ($t = H$) who have on average higher incomes.[14] In this model, which builds on a canonical quantitative commuting model á la Ahfeldt et al. (2013), location characteristics may be type-specific, which allows us to model significant differences in the desirability of different city locations. We then present a discussion of how endogenous price changes can lead either to gentrification or degentrification. We emphasize three parts to this process: first, if the infrastructure is desirable, it will increase demand to live and work in directly-affected areas, which is likely to cause endogenous increases in the prices of local non-tradeable goods. Second, net benefits – direct benefits combined with costs from price changes – may differ from direct benefits. If net benefits are negative for the poor, we will see gentrification. If they are negative for the rich, we will see degentrification.[15] Finally, the total welfare impact will depend on the characteristics (both fixed and endogenous) of other locations in the city to which either low or high types are displaced. We show how this process can be accommodated in a model and discuss different endogenous prices and mechanisms through which gentrification can occur. We end the section by showing how the change in the welfare of incumbent low and high types caused by the BRT can be calculated given a small number of parameters using exact-hat type formulas. As noted in the introduction, the exact hat approach allows us to generate counterfactuals without directly estimating the large number of type-specific fixed effects.

[14]The model is extremely easy to extend to a larger number of types, but we present the two type case for ease of notation.

[15]It is not possible that both high and low types see negative net benefits because that would imply lower demand to live in directly affected locations and would lower prices.

4.1 Basic Model: Worker Sorting

Our core model is a version of a canonical commuting model, building on Ahlfeldt et al. (2016), in which workers sort across a city characterized by heterogeneous productivities, amenities, and commuting costs, based on random preference or productivity shocks. There are a large number of people, half of whom are low types ($t = L$), and half of whom are high types ($t = H$).[16] These workers decide where to live and work over a set of locations. The utility of worker i of type t, who decides to live in location l and work in location w, is evaluated according to

$$U^t_{lwi} = \frac{\alpha^t_l c_i^{1-\beta^t} h_i^{\beta^t}}{\tau^t_{lw}} \epsilon^{a_t}_{lw}, \tag{1}$$

where α^t_l is the amenity of location l as experienced by a person of type t, c is units of consumption (measured in a numeraire), h is units of housing, τ^t_{lw} is the cost of commuting between l and w for a person of type t, and β^t measures the relative importance of consumption versus housing for people of type t. The term ϵ^a_{lw} (an lw amenity shock) captures reasons why the live/work location lw leads to high amenity; this parameter helps to better understand identification concerns in the model.

To model sorting across the city, we assume that each individual i draws a "live/work" location productivity shock z_{lwi}. This shock, which we assume is a permanent characteristic of the individual,[17] is drawn from a Fréchet distribution:

$$F^t(z_{lwi}) = \exp\{-E^t \epsilon^{\omega}_{lw} z_{lwi}^{-\theta}\},$$

and earnings in location w for an individual with shock z_{lwi} are given by

$$wage^t_{lwi} = \omega^t_w z_{lwi},$$

[16] In our empirical work, we use a World Bank poverty line to identify poor households. This leads to slightly more than 50% of the population being designated as poor. This difference is easy to incorporate in the model but ads significantly to notation, so we do not include it here.

[17] Later we relax this assumption looking at what happens if a proportion of the population redraws every period.

where ω_w is the wage per unit of human capital in location w. We assume that $E^H > E^L$ so that "high types" have higher mean productivity.[18] The term ϵ^{ω}_{lw} captures any reason why productivity may be higher for people who decide to live/work in location lw. This term, which we assume is exogenously set, allows for a clearer discussion of endogeneity issues when discussing identification.

Conditional on the choice of location lw, a worker of type t with shock z_{lwi} maximizes utility (1) subject to the requirement that $r^t_l h_i + c_i \leq \omega_w z_{lwi}$, where r^t_l is the residential rental rate in location i for housing suitable for a type t household. Solving this maximization problem gives rise to an indirect utility function:

$$V^t_{lw}(z_{lwi}) = \alpha^t_l \omega^t_w r_l^{-\beta^t} \left(\tau^t_{lw}\right)^{-1} z_{lwi}\epsilon^a_{lw} \equiv v^t_{lw} z_{lwi}. \tag{2}$$

This simple model leads to two key equations that govern the distribution of people across the city, and their earnings. First, a gravity commuting equation applies:

$$\pi^t_{lw} = \frac{\left(v^t_{lw}\right)^{\theta}}{\sum_{l'w'}\left(v^t_{l'w'}\right)^{\theta}} = \frac{\binom{t}{l}^{\theta}}{\Phi^t}, \tag{3}$$

where π^t_{lw} is the proportion of the type t population in the city that lives/works in location lw, and ϕ^t is proportional to the welfare of type t individuals. Second, a wage gravity equation holds:

$$\overline{wage}^t_{lw} = \Gamma\left(1 - \frac{1}{\theta}\right) E^t \omega^t_w \left(\pi^t_{lw}\right)^{-\frac{1}{\theta}} \epsilon^{\omega}_{lw} \tag{4}$$

where $\overline{wage}^t_{lw}$ is the average wage of those of type t who live in location lw and $\Gamma(\cdot)$ denotes the Gamma function.

4.2 Modelling (De-)Gentrification

As we noted above, we think of the (de-)gentrification process as having three important aspects: first, a piece of infrastructure may have heterogeneous direct value; second, endogenous changes in the prices of location-specific goods may be heterogeneous or

[18] Recall that the mean of a random variable with distribution F^t is given by $\Gamma(1-\frac{1}{\theta})E^t\epsilon^{\omega}_{lw}$.

have heterogeneous impacts; and third, the welfare costs dislocation will depend on the (potentially endogenous) characteristics of the locations to which dislocated households move. In this section, we show how the model can accommodate these processes.

4.2.1 Heterogeneity in the Value of Infrastructure

Suppose that, if prices remained constant, both low and high types would gain from a piece of infrastructure, but that low types would gain less. This could, for example, occur in the case of the BRT if low types are unable to afford the ticket price. This general increase in the value of living in areas close to the infrastructure will likely lead to an increase in demand for housing in the area and changes in prices, mostly notably rental price. This raises the possibility that, even if price changes have equal impacts on low and high types, the project could lead to a net loss for incumbent low types, a net gain for incumbent high types, and gentrification. A similar case could be made for degentrification.

We capture this possibility by allowing heterogeneity in the impact of the BRT on transport costs. We assume that transport costs τ^t_{lw} are type-specific and are a type-specific function of travel times:

$$\tau^t_{lw} = \left(\delta^t_{lw}\right)^{\eta^t},$$

where δ^t_{lw} is the type-specific travel time between l and w.

Throughout we denote a post BRT variable with a $\tilde{\cdot}$ and a prior to the BRT variable without a $\tilde{\cdot}$, so for example $\tilde{\delta}^t_{lw}$ is the post BRT travel time between l and w for those of type t, while δ^t_{lw} is the travel time prior to the BRT. We denote with a $\hat{\cdot}$ the ratio of post to pre-BRT variables, so that $\hat{\delta}^t_{lw} = \frac{\tilde{\delta}^t_{lw}}{\delta^t_{lw}}$. With this notation we have that the change in type-specific travel costs caused by the BRT is given by:

$$\hat{\tau}^t_{lw} = \left(\frac{\tilde{\delta}^t_{lw}}{\delta^t_{lw}}\right)^{\eta^t}.$$

This equation captures two reasons why travel cost reductions due to BRT may be type-specific: first, travel time changes may be heterogeneous. Second, the elasticity of travel cost to travel time may be heterogeneous.

4.2.2 Endogenous Local Prices

As highlighted above, endogenous changes in local prices is a key mechanism through which gentrification may occur. There are three ways in which this can happen. First, it may be that types respond differently to price changes (a demand side or preference channel); second, it may be that types face different prices and that those prices respond differently (a supply side channel); and finally as noted above even if price changes and responses are symmetric, heterogeneity in direct impacts may mean heterogeneity in net impacts after price change are accounted for. In this subsection, we discuss how we model endogenous price changes and how the model can capture the first two effects, with the third being addressed above.

We begin by discussing the supply-side response before turning to the demand side. A key equilibrium requirement in our model is that rental prices per unit of land are equal to total rental expenditures, divided by the total amount of land. This relationship can be written as:

$$r_l^t = \frac{R_l^t}{\rho_l^t T_l} \tag{5}$$

where $R_l^t = (1-\beta^t)\sum_w \overline{wage}_{lw}^t \pi_{lw}^t$ is the total expenditure on housing by individuals of type t in location l, and we allow for types to occupy different types of housing. We assume that all land can, without cost, be used to provide low type housing, but that it is costly to convert land to high type housing. We further assume that the cost of converting land to high type housing depends on the number of high type households living in the area. This allows for the possibility, for example, that the cost of converting land to high type is increasing as more marginal land is more costly to convert. Formally we assume

$$r_l^H = r_l^L \left(\pi_l^H\right)^{\lambda} \tag{6}$$

where $\pi_l^t = \sum_w \pi_{lw}^t$ is the total fraction of the type t population that lives in location l. Equation (6) allows for the possibility that high type rents rise faster than low type rents if $\lambda > 1$ or slower if $\lambda < 1$. $\lambda < 1$ would capture, for example, the case in which there is a constant per period cost of converting land to high quality, and so the gap between high and low rent becomes smaller as rental rates rise due to the arrival of more high types.

We allow for demand or preference effects to be heterogeneous by type in two ways. First, the indirect utility function (equation 2) allows for the possibility that low types spend a higher proportion of their income on housing than high types (i.e., $\beta^H \neq \beta^L$), implying heterogeneity in the welfare impact of rental price changes. Equation (3) then implies that this will lead to heterogeneity in location responses to equal proportional changes in rental rates. Second, we propose a more general possibility that low types are more sensitive to rental price changes, even if they spend the same percentage of income on housing. In particular, we allow for the possibility that amenity in location l is in part determined by rental rates. Low and high types have different preferences over the kinds of amenity created when rents rise. For example, if rent rises indicated a change toward a more affluent neighborhood, then high types may desire to live in high rent neighborhoods, while low types may not.[19] To capture this possibility we assume that $\alpha_l^t = \bar{\alpha}_l^t r_l^{-m^t}$ which means that the indirect utility function becomes

$$V_{lw}^t = \bar{\alpha}_l^t r_l^{-(m^t+\beta^t)} \omega_w^t \left(\tau_{lw}^t\right)^{-1} z_{lwi} \epsilon_{lw}^a. \tag{7}$$

We also allow for endogenous location-specific productivities, although we do not at this point allow this to be a source of (de-)gentrification because we assume that low and high type human capital are perfectly substitutable. In particular, we assume that there is a perfectly competitive market with a representative firm that has a production function:

$$Y_w = \bar{A}_w \left(\sum_t A_w^t Z_w^t \right)^{\alpha} T_w^{1-\alpha}$$

where $\bar{A}_w$ is total factor productivity in location w, Z_w^t is the total amount of type t human capital working in location w, A_t^w is the location-specific productivity of individuals of type t and T_w is the amount of land in location w available for production. We take T_w to

[19] This matches the definition of endogenous amenities in Couture et al. (2018).

be exogenous and not affected by the infrastructure project. The first order condition for maximizing profit taking ω_w^t (the wage per unit of human capital) as given is

$$\omega_w^t = \alpha \bar{A}_w A_w^t \left(\frac{\sum_t A_w^t Z_w^t}{T_w} \right)^{\alpha - 1} \equiv \alpha \bar{A}_w A_W^t \left(\frac{Z_w}{T_w} \right)^{\alpha - 1} \equiv A_w^t \omega_w \tag{8}$$

where Z_w is the total human capital in location w. This expression allows for a constant difference in productivity across types within a location, but implies that the the ratio of wage per unit of human capital $\frac{\omega_w^t}{\omega_w^L}$ is a constant.

4.2.3 Spatial Heterogeneity

This simple model features rich spatial heterogeneity by type, which allows us to capture key aspects of the gentrification question. Consider, for example, a place-based policy that leads the poor to be priced out of downtown areas. This may be compensated if the poor can move to high amenity locations previously occupied by the rich. However, if the poor do not value the same amenities as the rich, perhaps because they cannot afford complementary inputs such as cars required to enjoy suburbs, then this compensation cannot happen. Type heterogeneity in the α_l^t parameter allows for this possibility, and type heterogeneity in the transport cost parameter τ_{lw}^t can allow for differences in access to types of transport across space. We will see below that, despite this rich heterogeneity, we can take the model to the data without rich measures of type-specific amenity and transport costs. We also allow for rents r_l^t and productivities ω_w^t to be endogenous and type-specific as outlined in the above section.

4.3 Calculating the Welfare Impact of the BRT

The goal of the model is to help understand how the building of the BRT impacts welfare of those that live in the directly affected areas. In this section, we explain how the model can be used to achieve this goal. We allow for a single direct impact of the BRT: we take movement costs τ_{lw}^t to be exogenous but affected by the BRT. Let $\hat{\tau}_{lw}^t = \frac{\tilde{\tau}_{lw}^t}{\tau_{lw}^t}$ where˜again denotes a "post BRT" observation. We say that a location l is directly affected by the BRT if $\hat{\tau}_{lw} \neq 1$ for some w. We say that a worker is a poor incumbent if she is a low type and she lives in an area l that is directly affected by the BRT, with a rich incumbent similarly defined.

A very simple expression for total welfare changes (by type) from a change in transportation costs can be derived by applying Dekle et al. (2008)'s exact hat approach. Recall that Φ^t defined in equation (3) gives a measure of type-specific total welfare and let $\hat{\Phi}^t \equiv \frac{\tilde{\Phi}^t}{\Pi^t}$. It is straightforward to show that

$$\hat{\Phi}_t = \sum_{l,w} \pi^t_{lw} \left(\hat{\omega}^t_w \hat{r}_l^{-(m_t+\beta_t)} \left(\hat{\tau}^t_{lw}\right)^{-1} \right)^{\gamma} = \sum_{l,w} \pi^t_{lw} \left(\hat{v}^t_{lw}\right)^{\gamma}, \tag{9}$$

where $\hat{\omega}^t_{lw} \equiv \frac{\tilde{\omega}^t_{lw}}{\omega^t_{lw}}$, $\hat{\tau}^t_{lw} \equiv \frac{\tilde{\tau}^t_{lw}}{\tau^t_{lw}}$, and $\hat{r}^t_{lw} \equiv \frac{\tilde{r}^t_{lw}}{r^t_{lw}}$.

Formula (9) is useful for understanding the expected impact on welfare of the whole population, but our goal is to understand the change in welfare of those who are living in a location at the time of an intervention. We will first consider live/work locations lw and then generalize to living to locations l. Define welfare of those of type t who live/work in location lw prior to an intervention to be

$$\begin{aligned} W^t_{lw} &= v^t_{lw} \mathbb{E}_{F^t}(z_{lw} | \text{ chose } lw) & (10) \\ &= \Gamma\left(1 - \frac{1}{\gamma}\right) v^t_{lw} \left(\pi^t_{lw}\right)^{-\frac{1}{\theta}} & (11) \end{aligned}$$

As above, define $\hat{W}^t_o \equiv \frac{\tilde{W}^t_{lw}}{W^t_{lw}}$ where $\tilde{W}^t_{lw}$ is the after intervention welfare of those who were living in location lw prior to an intervention. To define a formula for $\hat{W}^t_{lw}$ we first relabel lw locations so each lw is given by a unique integer and $\hat{v}^t_1 < \hat{v}^t_2 < \ldots < \hat{v}^t_{NXN}$. We then show in Appendix C that:

$$\widehat{W}_{lw}^{t} = \frac{1}{\pi_{lw}^{t}} \left(\sum_{d=1}^{lw-1} \pi_{d}^{t} \left(\hat{v}_{d}^{t}\right) \sum_{j=d}^{lw-1} \frac{\pi_{lw}^{t}}{\sum_{i=j+1}^{N} \pi_{i}^{t}} \left[\left(\frac{\left(\hat{v}_{d}^{t}\right)^{\theta}}{\sum_{i=1}^{j} \pi_{i}^{t} \left(\hat{v}_{i}^{t}\right)^{\theta} + \left(\sum_{i=j+1}^{N} \pi_{i}^{t}\right) \hat{w}_{j+1}^{\theta}} \right)^{\frac{\theta-1}{\theta}} - \left(\frac{\left(\hat{v}_{d}^{t}\right)^{\theta}}{\sum_{i=1}^{j} \pi_{i}^{t} \left(\hat{v}_{i}^{t}\right)^{\theta} + \left(\sum_{i=j+1}^{N} \pi_{i}^{t}\right) \hat{w}_{j}^{\theta}} \right)^{\frac{\theta-1}{\theta}} \right] + \pi_{lw}^{t} \left(\hat{v}_{lw}^{t}\right) \left[\left(\frac{\left(\hat{v}_{lw}^{t}\right)^{\theta}}{\sum_{i=1}^{lw} \pi_{i}^{t} \left(\hat{v}_{i}^{t}\right)^{\theta} + \sum_{i=lw+1}^{N} \pi_{i}^{t} \left(\hat{v}_{lw}^{t}\right)^{\theta}} \right)^{\frac{\theta-1}{\theta}} \right] \right) \tag{12}$$

where $\hat{v}_{lw}^{t} = \hat{\omega}_{w}^{t} \hat{r}_{l}^{-(m^{t}+\beta^{t})} \left(\hat{\tau}_{lw}^{t}\right)^{-1}$. We then define

$$\widehat{W}_{l}^{t} = \sum_{w} \pi_{lw}^{t} \widehat{W}_{lw}^{t} \tag{13}$$

to be the change in welfare for those who were living in location l prior to the BRT.

Equations (12) and (13) will be fundamental to our approach, and deserve some explanation. Equation (13) is simply a weighted average of (12) so long as we know the ex-ante location choices by type, while (12) says that to determine how a place-based policy affects the welfare of those living in an affected location, it is necessary/sufficient to know the ex-ante live/work choices of people by type, the changes in v_{lw}^{t} "caused" by the policy and the sorting parameter γ. We will always assume that it is possible to know the direct impact of a policy, so for example, in our application to the BRT, we will assume that $\hat{\tau}_{lw}^{t}$ is known. The upshot of this is that we need a method to determine the endogenous changes in ω_{w}^{t} and r_{l}^{t}. We turn to these now, first considering $\hat{\omega}_{w}^{t}$, then $\hat{r}_{l}^{t}$.

To derive a usable expression for $\hat{\omega}_{w}^{t}$ we start with equation (8. Given this expression, and our assumption that A_{w}^{t} is exogenous, it is clear that $\widehat{\omega}_{w}^{t} = \widehat{\omega}_{w}$ for all t and so we concentrate on deriving an expression only for $\widehat{\omega}_{w}$. We have

$$\widehat{\omega}_{w} = \widehat{Z}_{w}^{\alpha-1}$$

and from (4) we can determine the total amount of human capital as:

$$\begin{aligned}
\widehat{Z}_w &= \frac{\sum_t A_w^t E^t \sum_l \pi_{lw}^{\frac{\theta-1}{\theta}}}{\sum_t A_w^t E^t \sum_l \tilde{\pi}_{lw}^{\frac{\theta-1}{\theta}}} \\
&= \sum_{t,l} \Delta_{lw}^t \left(\hat{\pi}_{lw}^t\right)^{\frac{\theta-1}{\theta}} \\
&\Rightarrow \; \widehat{\omega}_w = \left(\sum_{t,l} \Delta_{lw}^t \left(\hat{\pi}_{lw}^t\right)^{\frac{\theta-1}{\theta}}\right)^{\alpha-1} \qquad (14)
\end{aligned}$$

where Δ_{lw}^t is the proportion of total human capital that works in location w that is of type t and comes from location l.

Much like equation (9) above, this equation states that changes in productivities are a simple function of the amount of human capital that was initially working in a location, multiplied by the change in the population induced by the change. From above we know $\Delta_{lw}^t = \Gamma(1-\frac{1}{\theta})\left(\pi_{lw}^t\right)^{-\frac{1}{\theta}}$ which we can calculate given knowledge of θ and π_{lw}^t. The commute matrix π_{lw}^t is generally observable in data and we discuss below how to identify θ. To determine $\hat{\omega}_w^t$ it remains to find an expression for $\hat{\pi}_{lw}^t$. This, fortunately is simply to calculate from (3)

$$\hat{\pi}_{lw}^t = \frac{\left(\widehat{\omega}_w \widehat{r}_l^{-(\gamma_t+\beta_t)} \left(\widehat{\tau}_{lw}^t\right)^{-1}\right)^\theta}{\sum_{l',w'} \pi_{lw}^t \left(\widehat{\omega}_{w'} \widehat{r}_{l'}^{-(\gamma_t+\beta_t)} \left(\widehat{\tau}_{l'w'}^t\right)^{-1}\right)^\theta}. \qquad (15)$$

We will show in a second that this equation can be combined with others in a recursive form and solved.

To determine $\hat{r}_l^t$ we first solve for ρ_l^t (the proportion of residential land in location l devoted to type t housing) using equations (6) and (5), before subbing back in to (6) to get

$$r_l^H = \frac{R_l^L(\pi_l^H)^\lambda + R_l^H}{T_l} \quad \text{and} \quad r_l^L = \frac{R_l^L(\pi_l^H)^\lambda + R_l^H}{(\pi_l^H)^\lambda T_l} \qquad (16)$$

where you will recall that R_l^t is the total rent expenditure by those of type t living in location l. From this equation we have

$$\begin{aligned}\hat{r}_l^H &= \frac{R_l^L(\pi_l^H)^\lambda \hat{R}_l^L(\hat{\pi}_l^H)^\lambda + R_l^H \hat{R}_l^H}{R_l^L(\pi_l^H)^\lambda + R_l^H}, \text{ and} \\ \hat{r}_l^L &= \frac{R_l^L(\pi_l^H)^\lambda \hat{R}_l^L(\hat{\pi}_l^H)^\lambda + R_l^H \hat{R}_l^H}{(\hat{\pi}_l^H)^\lambda R_l^L(\pi_l^H)^\lambda + R_l^H}. \end{aligned} \tag{17}$$

Finally, it is straightforward to show that

$$\hat{R}_l^t = \frac{\sum_w \tilde{\omega}_w^t \left(\tilde{\pi}_{lw}^t\right)^{\frac{\theta-1}{\theta}} \epsilon_{lw}^{\omega}}{\sum_w \omega_w^t \left(\pi_{lw}^t\right)^{\frac{\theta-1}{\theta}} \epsilon_{lw}^{\omega}} = \sum_w \chi_{lw}^t \widehat{\omega}_w \left(\widehat{\pi}_{lw}^t\right)^{\frac{\theta-1}{\theta}} \tag{18}$$

where χ_{lw}^t is the proportion of earnings of type t households who live in l that is earned in work location w. We show later that this is observable in data.

To summarize, we began by showing that location-specific welfare changes by type could be calculated knowing only the live/work locations by type, the exogenous change in transport costs (or other policy) and endogenous changes in location-specific productivities and rental rates. This is shown in equation (12). We then showed how to determine these two things. This gives us three equations: (15), (14) and (17). These equations have a recursive structure: Equation (15) shows us that we can write the change in location choices ($\hat{\pi}_{lw}$) as a function of data and endogenous changes $\hat{\omega}_w$ and $\hat{r}_l^t$. Equation (17), when combined with equation (18), shows that determining $\hat{r}_l^t$ require us to know both $\hat{\pi}_{lw}^t$ and changes in $\hat{\omega}_w$. Finally, (14) shows that $\hat{\omega}_w$ can be written a function only of $\hat{\pi}_{lw}^t$. Hence it is possible to substitute equations (17) and (14) in to equation (15) to recover a series of (nonlinear) equations that feature only $\hat{\pi}_{lw}^t$. It is easy to show that the resulting equation is HD(1) and, therefore, can be uniquely solved when we impose the requirement that the probability changes sum to one.

5 Model Simulations

This section shows that our baseline model can generate rich patterns of spatial equilibria in the city. To illustrate the mechanics of the model, we consider a simplified urban setting, with three locations: a rich-productivity/rich-amenity downtown, a poor-productivity/poor-amenity slum, and a a poor-productivity/rich-amenity suburb. To develop intuition, we start by considering the equilibrium effects of improving the amenity in the slum. A transportation improvement is equivalent to a pair-level (e.g., slum to CBD and CBD to slum) amenity. The figure below illustrates the set-up.

In a series of simulations, we show that the model, while simple, accommodates a wide range of possible impacts from improving the quality of the slum. Concentrating on the cases with two types ("rich and poor") we show that it is possible to get outcomes ranging from no gentrification (poor are not displaced) to strong gentrification (the initial poor are displaced in absolute numbers).[20] We define three types of gentrification, based on the change in the ratio of poor to rich residents, as follows:

1. No gentrification: the ratio of poor to rich types in a neighborhood stays constant, $\Delta \frac{L}{H} = 0$.

2. Weak gentrification: the ratio of poor to rich types in a neighborhood decreases, but the number of poor types (weakly) increases; $\Delta \frac{L}{H} < 0; \Delta L \geq 0$.

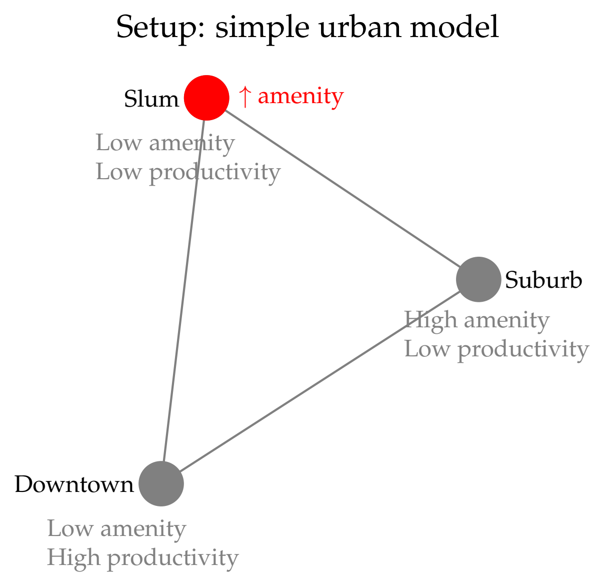
3. Strong gentrification: the ratio of poor to rich types in a neighborhood decreases and the number of poor types decreases; $\Delta \frac{L}{H} < 0; \Delta L < 0$. Strong gentrification can either be:

    a) Compensated: the utility of the displaced poor increases

    b) Uncompensated: the utility of the displaced poor decreased

The model is quite capable of delivering a "gentrification effect" where the poor benefit much less than the rich, as well as an "public goods effect" where the poor benefit more than the rich. The outcome will, therefore, be an empirical question.

[20] The model is equally as rich in generating a range of aggregate outputs – the rich can gain more than the poor; the poor gain more than the rich; and for the poor to lose in an absolute sense, while the rich gain.



5.1 Simulations

We vary the degree of nonhomotheticity between poor and rich types to generate the four different distributional outcomes. Table 7 gives the parameters used in the simulation for each case.

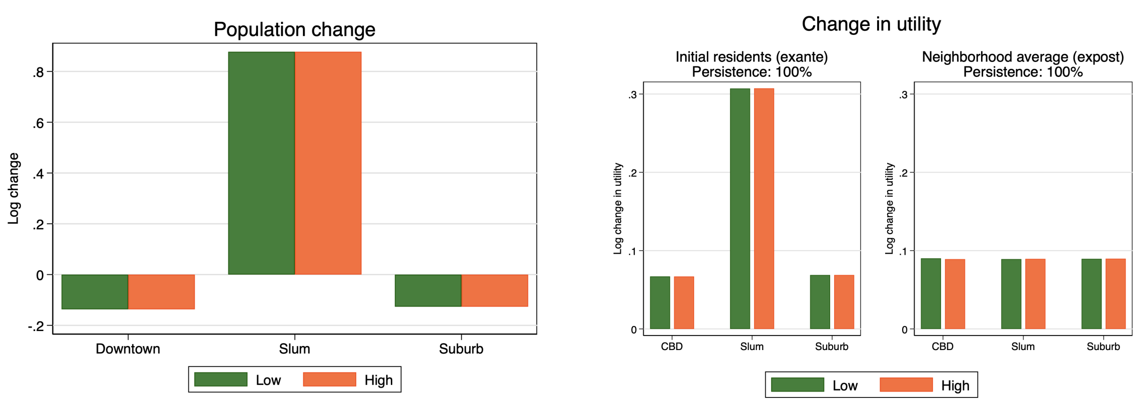
Table 7: Parameters used in model simulations

Case	Income share on housing $(1-\beta)$	Endogenous amenity (m)
No gentrification	$\beta_l = 0.5; \beta_h = 0.5$	$m_l = 0$
Weak gentrification	$\beta_l = 0.2; \beta_l = 0.5$	$m_l = 0$
Strong gentrification, compensated	$\beta_l = 0.2; \beta_l = 0.5$	$m_l = -0.5$
Strong gentrification, uncompensated	$\beta_l = 0.2; \beta_l = 0.5$	$m_l = -1.8$

5.1.1 No gentrification

The left panel of Figure 2 shows the change in the population share living in each of the three neighborhoods after the slum beautification project. The proportional inflows of rich and poor types are equivalent, so the population ratio between poor and rich is unchanged. The panel of the right shows the welfare effects of this project. The first part of the figure shows the utility for *initial* residents, i.e., those living in each neighborhood before the policy change was implemented. This figure shows that the initial population received a welfare gain of 30%. Residents in other neighborhoods indirectly benefited from the project through GE effects; their benefit was 8%. The second part of the figure shows the change in utility between inhabitants of each neighborhood in the pre period and inhabitants of each neighborhood in the post period. This figure thus contains information of the effects of the policy both at the neighborhood level and the changing composition of the residents in each neighborhood. The Frechet model has a knife-edge property that endogenous sorting exactly offsets higher indirect utility; this property is present in the figure in the right which shows that once individuals resort (i.e., the data is now a repeated cross-section of individuals) the change expected welfare is equalized across location.

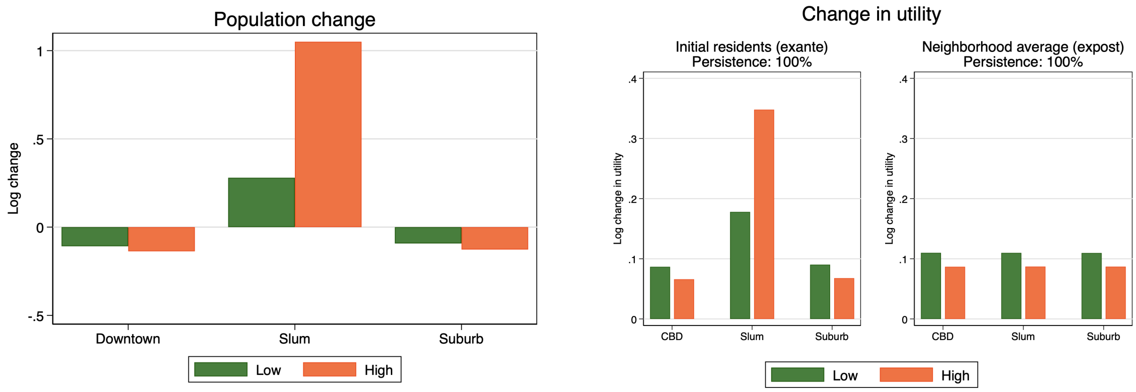
Figure 2: Model simulation (a): No gentrification



5.1.2 Weak gentrification

Figure 3 introduces nonhomotheticities between poor and rich types. Low types now spend a larger share of their income on rent, and so are more affected when the rents in the slum increase after the beautification project. For the specific parameters we use, poor types still move into the slum, but proportionally less than rich types. As a result, the population ratio falls, as shown on the left panel. The panel on the right shows the utility for initial residents. Initial rich residents of the slum benefit more than initial poor residents; outside the slum, initial poor benefit more than rich. Again, the repeated cross-section figure shows that ex-post welfare gains at the neighborhood level are equalized.

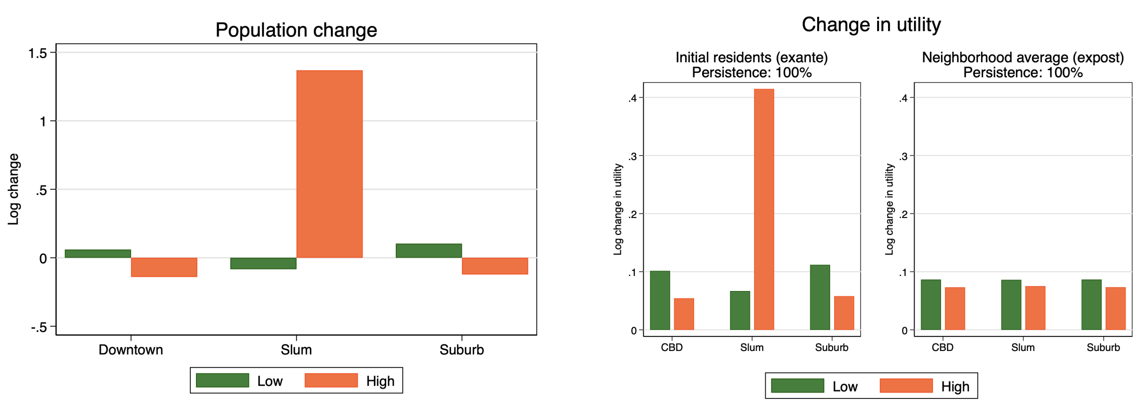
Figure 3: Model simulation (b): Weak gentrification



5.1.3 Strong gentrification: compensated

Figure 4 introduces an additional nonhomotheticicities between poor and rich types through an endogenous amenity. As the rent increases, amenities become less desirable to poor types. In this case, there is an absolute reduction in the number of poor types living in the slum and a reduction in the population ratio between rich and poor. In this case, the largest welfare gains again go to the initial rich who are living in the slum, but the displaced poor are compensated because the change in GE prices (e.g., lower rents) when they move to the suburb or the CBD is large enough to compensate for their displacement.

Figure 4: Model simulation (c): Strong gentrification: compensated

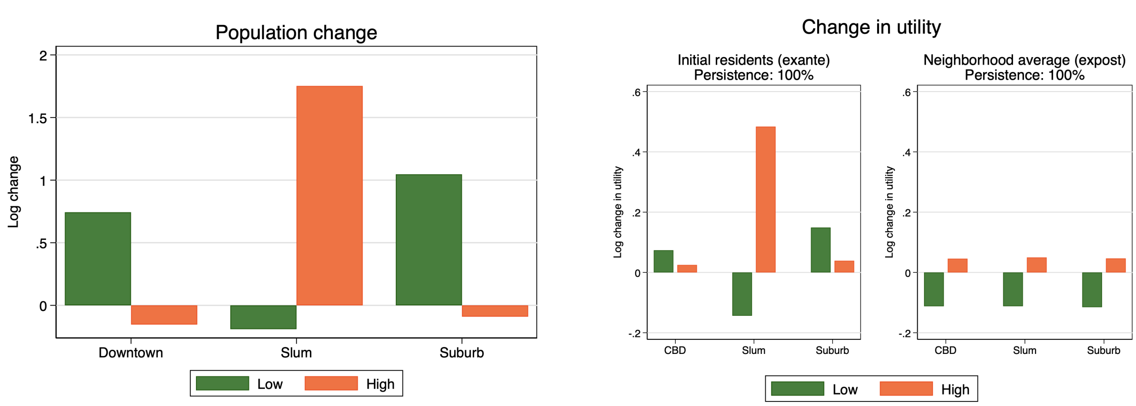


5.1.4 Strong gentrification: uncompensated

Finally, Figure 5 illustrates an extreme case where the negative externality of higher rents onto the poor is very large. The initial poor who are living in the slum face a negative welfare loss after the slum upgrading policy. This occurs because the GE adjustments (lower rents and higher wages) are not large enough to compensate them for moving out of the location where they initially had a high comparative advantage (or a very strong preference). Overall, this particular parameterization generates that low types on average across the whole city face a decrease in welfare.

These simulations highlight that the model is capable of generating a wide range of outcomes. The particular outcome will depend largely on the parameters determining the difference – whether through expenditure shares and/or endogenous amenities – between low and high types, and so will ultimately be an empirical question. We now turn to our empirical setting and discuss the model's mapping to parameter estimation and computation of the welfare changes.

Figure 5: Model simulation (d): Strong gentrification: uncompensated



6 Model estimation

This section estimates the endogenous parameters of the model. It discusses the implications of these estimates for the potential channels of gentrification and degentrification introduced in the model in Section 4. Table 8 lays out the endogenous parameters and summarizes their interpretation.

The estimation uses data at the level of 52 spatial units across our study area, constructed from wards (the lowest level administrative subdivision in Tanzania) as described in Appendix D.

Table 8: Model parameters

Parameter	Name	Explanation
Commuting response		
θ^t	Commuting elasticity	Drives comparative advantage: inverse of the variance of the Frechet distribution
ϵ^t	Traveltime elasticity	Elasticity of utility to changes in travel time
$d_{lwt} = f^t(z_{lwt})$	First stage regression	Responsiveness of traveltime to the BRT
Housing market response		
λ	Integration in housing market	How integrated is the housing market for the rich and poor? How much do rents comove?
β^t	Share of income on housing	
m	Rent externality	Whether low-types are more affected by a change in rents

6.1 Commuting response

The gravity model is:

$$\pi^t_{lwt} = \frac{\left(B_{lt} w_{wt} r_{lt}^{-(m^t+\beta^t)} (d^t_{lwt})^{\epsilon^t}\right)^{\theta^t}}{\sum_{i,j}\left(B^t_{lt} w_{wt} r_{lt}^{-(m^t+\beta^t)} (d^t_{lwt})^{\epsilon^t}\right)^{\theta^t}}$$

The gravity regressions highlight the three commuting channels through which high and low types may differ: (i) travel time, d^t_{lwt}; (ii) the elasticity between travel time and utility, ϵ^t; and (iii) the commuting elasticity, θ^t.

To estimate the effect of the BRT on travel times, we run the following regression, which is equivalent to running a first-stage regression of the predicted effect of the BRT on travel times:

$$\log \text{actual travel time}_{lwt} = \beta \log \text{BRT instrumented travel time}_{lwt} + \epsilon_{lwt} + \text{other FE} \quad (19)$$

To estimate the commuting and travel time elasticities, we note that that the model implies the following two regressions, which yields a method to identify ϵ and θ separately:

Commuting gravity:

$$\log \pi^h_{lwt} = \alpha_{lt} + \alpha_{wt} + \theta^h \epsilon^h \log d^h_{lwt} + \epsilon_{lwt} \quad (20)$$

Wage gravity:

$$\log \text{wage}^h_{lwt} = \alpha_{lt} + \alpha_{wt} - \frac{1}{\theta^h} \log \pi^h_{lwt} + \epsilon_{lwt} \quad (21)$$

The results for these regressions are in Table 9. Column (1) shows a positive correlation between actual travel time, computed from the household data, and the predicted instrument that accounts for the effect of the BRT. Columns (2)-(4) estimate the commuting gravity relationship. We show that commuting shares are negatively correlated with observed travel time (Column (2)), the instrument (Column (3)), and actual traveltime instrumented by predicted travel time (Column (4)). Column (5) shows that wages decrease with the share commuting. Together, these imply estimates of $\theta = 4.7$ and $\epsilon = 0.15$.

We repeat the exercise allowing the parameters to vary by type in Appendix Table A11. We find no statistically significant effect of a stronger first stage for high types (Column (1)), no differential estimate in the commuting gravity (Column (4)) but a significant interaction for wage gravity (Column (5)), with the estimated elasticity overall estimated to be -0.15 and an interaction effect for high types of -0.06, yielding that high types have an overall elasticity of -0.21. The larger elasticity implies a smaller θ, which is inversely proportional to comparative advantage, i.e., high types have a larger scope for comparative advantage than low types.

Table 9: Estimation of commuting parameters (type defined by WB 5.50 poverty line hybrid)

	First-stage Dep var: log actual travel time	Commuting gravity Dep. var: log commuting share			Wage gravity Dep. var: log wage
	(1)	(2)	(3)	(4)	(5)
Log traveltime instrument (Phase 1)	0.395		-0.491		
	0.087***		0.139***		
Log actual travel time		-0.234		-1.397	
		0.069***		0.529**	
Log commuting share					-0.214
					0.040***
F stat	20.707				
N	747	852	843	747	678
Estimator	FS	OLS	OLS	2SLS	OLS
origxyr	✓	✓	✓	✓	✓
destxyr	✓	✓	✓	✓	✓
origxdest	✓	✓	✓	✓	✓
theta					4.663
thetaeps				0.716	
impliedeps				0.154	

Notes: High type is hybrid above WB 5.50 poverty line based on expenditure (incl. imputed rent) per capita. Sample is commuting choices between 52 origins and 52 destinations. Orig-yr and dest-yr fixed effects computed at the 52 level. Pair fixed effects computed at the 5 level. Predicted travel time is populated for all pairs. Actual travel time comes from the survey data and is only populated for pairs with positive flows. Sample is all. Standard errors clustered at the pair level.

6.2 Housing market response

In this section, we consider the potential gentrification channels introduced in the model that operate through the housing market. We first consider evidence on the integration between the housing market for the rich and poor and their expenditure shares on housing and then consider whether as well as whether there is evidence for an endogenous amenity response.

6.2.1 Integration of housing market between low and high

We start by asking whether the rich and poor live in the same housing. To do so, we run hedonic regressions that regress the reported rent per room in the house on observable characteristics of the house and a dummy variable for the household living in the structure being a high type.

Table 10 reports the results. Column (1) reports a hedonic regression using expected rent. The signs on most characteristics are as expected; for instance, rents are higher for houses with non-latrine toilets, electricity, and non-wood cooking. However, even controlling for structure characteristics, high consumption households spend 33% more per room. Column (2) includes location fixed effects to control for differential sorting of types across wards and still finds a significant effect. Column (3) includes building fixed effects. The point estimate implies that when a high type moves into the building, the rent per room increases by 34%.[21] This suggests that the housing market in Dar is segmented: there are some low-quality houses, where primarily low-income households reside. There are some high-quality houses where high-income households reside. A building can switch from housing low-income residents to high-income residents, but rents increase when it does so.

Given the evidence for segregated housing markets, do the average rents experienced by low- and high-income households comove? Table 11 regresses the log average rent (either paid or expected) for low types on the log average rent (either paid or expected) for high types. We see weak evidence that the two comove.

6.2.2 Share of expenditure on rent

We have established that richer households pay higher rent to live in a house. How does this relate to their overall consumption of housing? Evidence on the housing share of expenditure comes directly from the survey data. Table 12 tabulates household budget shares by type in the baseline survey. We compute spending on eight expenditure categories, using imputed rent for landlords.[22] Column (1) and (2) show that high types spend 19% of their expenditure on housing, while low types spend 14%. The lower housing expenditure share for low types is explained by the fact that low types spend a larger proportion of their income, 49% vs. 41%, on food. We show in Appendix Table A13 that the finding that lower-consumption households spend proportionally less on housing is robust across several methods of measuring expenditure.[23]

[21] Appendix Table A12 report the analysis with paid rent and find the same pattern, with high types consistently paying higher rents per room.

[22] The precise survey question we ask is: "Assume you want to rent the x rooms of this dwelling that are occupied by your household (with no equipment). What would be a real monthly rent for each room?" This question is asked to both renters and owners.

[23] We compute the same table across several countries in Appendix Table A14 and find that this pattern – that housing expenditure shares for the poor are below or equal to those of the rich – holds across very poor countries where food expenditure shares are high (e.g., Kenya, Tanzania, and Uganda), but not in more affluent countries where food expenditure shares are lower (e.g., Colombia and the USA).

Table 10: Hedonic rent regressions (bl mu) (type defined by WB 5.50 poverty line hybrid)

	(1)	(2)	(3)
Dep var: log expected rent per room			
Electricity in house for lighting	0.372	0.305	
	0.030***	0.032***	
Street has lights	-0.076	0.029	
	0.056	0.060	
Road is paved	0.111	0.137	
	0.034***	0.036***	
HH uses non-latrine toilet	0.179	0.202	
	0.028***	0.029***	
HH has piped water	0.083	-0.003	
	0.026***	0.027	
HH has non-wood cooking	0.334	0.291	
	0.033***	0.034***	
HH has cement walls	0.130	0.157	
	0.066**	0.068**	
HH has slate roof	0.505	0.486	
	0.181***	0.176***	
High type	0.331	0.248	0.344
	0.027***	0.028***	0.029***
HH owns building	-0.028	0.030	
	0.026	0.026	
N	3277	3277	3277
N struc	2075	2075	2075
locFE	X	✓	✓
strucFE	X	X	X
yrFE	✓	✓	✓

Notes: High type is hybrid above WB 5.50 poverty line based on expenditure (incl. imputed rent) per capita. Regression weighted by hh weight.

Table 11: How integrated is the housing market? (type defined by WB 5.50 poverty line hybrid)

Dep var: log average rent (paid/exp/spend) per room (l)	(1) All	(2) All	(3) Bal	(4) Bal
Log avg rent paid per room (h)	0.090		-0.084	
	0.127		0.376	
Log avg rent exp per room (h)		0.130		0.274
		0.120		0.115**
N	72	100	38	100
locFE	✓	✓	✓	✓
timeFE	✓	✓	✓	✓

Notes: Average rent per room for L and H. An observation is a location (n=52) by time (n=2).

6.2.3 Endogenous amenity

To estimate the endogenous amenity response we examine the indirect valuation of the neighborhood. We note that the commuting gravity equation implies:

$$\log \pi^t_{lwt} = \underbrace{-(\beta^t + m^t)\log r^t_{lwt} + B_{lwt}}_{\alpha^t_{lt}} - \beta \log d_{lwt} + \gamma_{wt} + \epsilon_{lwt}$$

We proceed by estimating the origin-type-year fixed effect and then estimating the (differential) responsiveness to rent, following other papers in the literature (e.g., Diamond (2016)). We then decompose the estimated fixed effect to estimate the elasticity of indirect utility to rent by estimating the following equation:

$$\log \alpha^t_{lt} = \log r^t_{lt} + \beta \mathbb{I}(t = h) \times \log r^t_{lt} + \gamma_{lt} + \gamma^t + \epsilon^t_{lt}$$

The coefficient on the interaction term is equivalent to $(\beta^L - \beta^H) + (m^L - m^H)$. It measures how less costly, either through spending a smaller proportion of their income on housing or a smaller effect of endogenous amenities, high types find higher rents than low types. A positive coefficient means that the rich find higher rents less costly than the poor. A positive coefficient thus suggests a gentrification channel. The results are in Table 13. Column (1) estimates the equation using the average rent. Column (2) estimates the

Table 12: Share of total expenditures (type defined by WB 5.50 poverty line hybrid), post is 0

	(1) Low type	(2) High type
Food	0.49	0.41
	(0.16)	(0.16)
Utilities	0.08	0.08
	(0.05)	(0.06)
School	0.04	0.05
	(0.06)	(0.10)
Transit	0.10	0.10
	(0.07)	(0.08)
Health	0.05	0.05
	(0.05)	(0.05)
Clothing	0.08	0.09
	(0.09)	(0.08)
Other	0.01	0.02
	(0.04)	(0.04)
(Imputed) rent	0.15	0.19
	(0.12)	(0.16)
N	990	731
Mean monthly per capita (implied) expenditure	109,674	286,419

Notes: High type is hybrid above WB 5.50 poverty line based on expenditure (incl. imputed rent) per capita. The unit of analysis is the household (expenditure values are simple averages of the expenditure amounts reported by all individual respondents in the household). The denominator includes imputed rent. Statistics weighted by computed sample weights.

elasticity to the average rent experienced by each type, and we find an elasticity of 0.34. Given that the poor spend 4% less on housing than the rich, this parameter is interpreted as the poor finding higher rents 38% more costly (i.e., through endogenous neighborhood change) than the rich.

Table 13: Estimating the m parameter (type defined by WB 5.50 poverty line hybrid)

	Fixed effect: linear IV		Fixed effect: RF PPML	
	(1)	(2)	(3)	(4)
High type × Log avg rent	0.733		1.238	
	0.189***		0.298***	
High type × Log rent (avg by type)		0.343		0.730
		0.155**		0.246***
N	140	140	170	170
locFE				
pdFE				
locxpdFE	✓	✓	✓	✓

Notes: High type is hybrid above WB 5.50 poverty line based on expenditure (incl. imputed rent) per capita. Rent used is BL/MU. An observation is a location x pd x type. Observations missing if we can't identify the origin x year fixed effect. Standard errors clustered by ward (n=52).

6.3 Taking stock

The estimation results in this section provide evidence on the strength of the key channels for infrastructure-induced gentrification and de-gentrification introduced in the model in Section 4.

The results suggest that the BRT may have introduced gentrification pressures via two of these channels. First, the results in Subsection 6.1 suggest that the BRT had stronger commuting effects for high versus low types. Second, the endogenous amenity response estimated in 6.2.3 suggests that low types may be more sensitive than high types to the BRT-induced rental rate increases documented in Section 3. Set against this, the parameter estimates also raise the possibility of offsetting de-gentrification mechanisms playing an important role. The fact that expenditure shares on housing are higher for the rich than the poor, as documented in Section 6.2.2, provides one such channel. It is also possible that segregated housing markets may contribute to a stronger out-migration response of high types to rental rate increases due to supply-side forces.

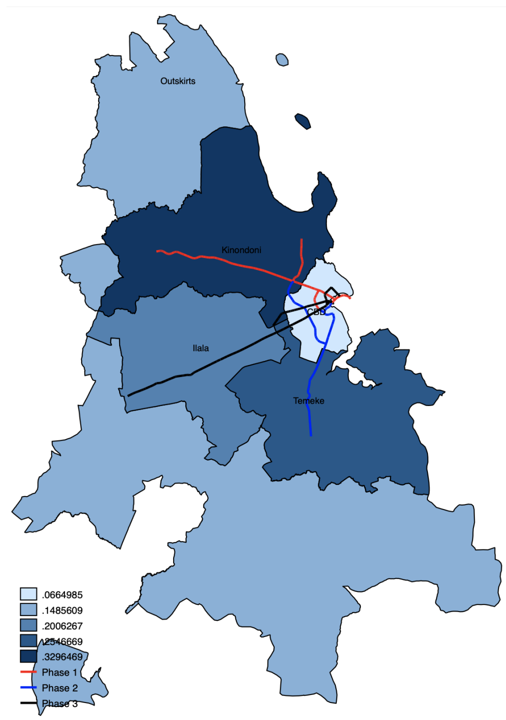
The next section uses these parameter estimates and our survey data to estimate the overall welfare effect of the BRT on poor incumbent residents through the lens of the model. This also allows us to estimate the BRT's impacts on high and low types throughout the city as subsequent phases of the BRT system are implemented.

7 Welfare gains of the BRT

This section implements our procedure for the Dar es Salaam BRT. We focus on understanding the effect of the BRT on the incumbents in each location. A strength of the approach is it can also predict the welfare effects of future phases, given the baseline data and values of parameter estimates. We thus present results for Phase 1 – the phase that is currently operational – and predictions for the remainder of the system (Phases two through six) that will be constructed in the future.

For the results in this section, we aggregate the 52 wards to five augmented districts: the three districts of Dar es Salaam (Kinondoni, Ilala, and Temeke), separating the CBD and then defining locations further than 15 km from the CBD as the "outskirts." Phase One of the BRT is built in Kindondoni; Phases Two and Three are scheduled to be built in Temeke and Ilala respectively. The five aggregated areas are shown in Figure 6.

Figure 6: Dar es Salaam: 3 districts + CBD/outskirts



To implement the method, we use the estimated values for parameters. We summarize the parameters and the values we employ in the table below. Note that the current estimation does not allow for either segregated markets or an endogenous amenity effect; thus, the results should be treated as preliminary.

Exact hat: parameter values

Parameter	Explanation	Source	Value
H_h	Number of high types	Share above median	0.5
H_l	Number of low types	Share below median	0.5
fs^l, fs^h	Strength of first-stage on traveltime (by type)	From commuting response	{0.527, 0.541}
θ^l, θ^h	Migration elasticity (by type)	From commuting response	{5.487,4.76}
ϵ^l, ϵ^h	Traveltime elasticity (by type)	From commuting response	{0.265, 0.239}
β^l, β^h	One minus the share of income on rent (by type)	Data	{0.85,0.81}
m_l	Negative rent multiplier for l	Set to zero	0
λ	Integration between high and low rental market	Set to zero	0
α	Production share of human capital	Literature	0.65

7.1 Gentrification effects of Phase 1

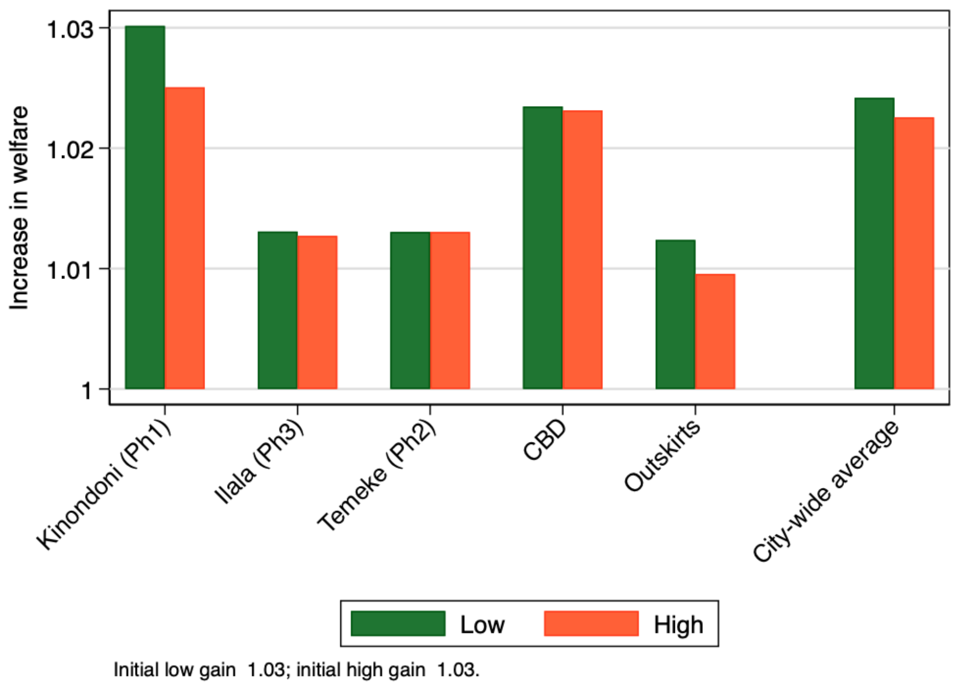
Figure 7 plots the welfare gain for residents by where they were living before the construction of the BRT. The residents of Kinondoni, the district where Phase 1 was constructed, had larger welfare gains on average than residents of other locations. The initial poor saw an increase of 3% (compared with an average gain of 2.4% for the poor across the whole city). Initial rich saw a rise in welfare of 2.5%, compared to an average increase of 2.3% across the city. We do not find gentrification effects of Phase 1: initial poor incumbents gained in an absolute sense from the BRT phase 1.

7.2 Gentrification effects of Phases 2-6

Figure 8 plots the same computation – the gain in welfare for people based on where they initially live – cumulatively for Phases two through six.[24] The panel on the left plots the welfare gain for the incumbent poor. We find that the overall gain differs by region: Kinondoni and the CBD, which become the most densely connected, face the

[24]For each phase we are computing the change in welfare based on the location in the period before the construction of Phase 1 of the BRT.

Figure 7: Estimated welfare gains of Phase 1 for incumbents in each district



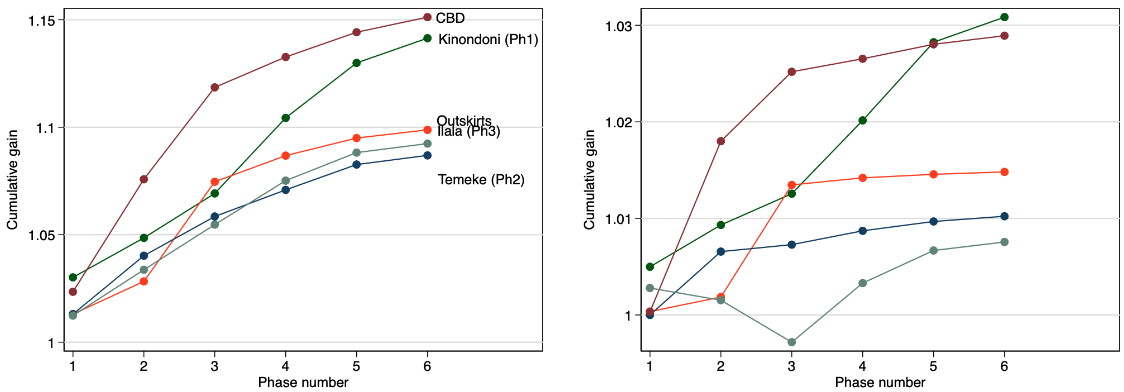
Notes: Figure plots the welfare gain by origin location for high and low.

largest cumulative gains for the incumbent poor of close to 15%. Ilala, Temeke, and the outskirts receive a 10% gain at the completion of the system.

The panel on the right plots the gain faced by low incumbents relative to the gain faced by high incumbents. A number below 1 means that the low benefited relatively less than the poor. Overall, we find that the incumbent poor will benefit more than the incumbent rich throughout the system's introduction. An exception is people who live in Ilala, the location of Phase 3. We predict that the poor living in Ilala will gain from the BRT, but the proportional gain from the introduction of Phase 3 of the system will be approximately 1% larger for the rich than the poor. This pattern will reverse with the introduction of the later phases of the system. Overall, we find evidence that both Phase 1 and the future Phases of the BRT will be pro-poor.

Figure 8: Cumulative welfare gains of Phases 1-6 by initial location and type

(a) Welfare of low (b) Welfare of low / welfare of high



Notes: Figure plots the welfare gain by origin location for high (dashed line) and low (solid line).

7.3 Decomposition of gentrification

What explains the difference in average gains to poor and rich incumbents? We decompose the channels in Table 14. The baseline estimates show that poor incumbents face a gain of 3%, compared with a gain of 2.5% to rich incumbents. The net effect of the commuting parameters (the elasticity to travel time, the first stage effects, and the migration elasticity) is slightly pro-poor: giving the rich the same parameters as the poor would lead to larger gains (3.1%) for the rich than the poor (2.9%). The housing market effect (currently only the difference in expenditure shares) has a negligible impact on welfare. Finally, the initial distribution of types – measured by the commuting shares – is pro-rich. If we assume instead that the work-live patterns of the rich are the same as the poor, then we estimate a lower welfare gain for the rich – 2.1% compared with 2.5% under the realized live-work patterns. This is reflecting the fact that Phase 1 serviced an area with relatively wealthy inhabitants.

8 Conclusion

Roads, rail, and other public transport in a city are "place-based," in that they are built in specific neighborhoods. Do such investments benefit the poor? If people are mobile

Table 14: Decompose welfare gain from Ph 1

	Incumbents near Ph. 1		Average across city	
	Low	High	Low	High
Baseline estimates	1.030	1.025	1.024	1.023
Equalize commuting market effect	1.029	1.031	1.025	1.027
Equalize housing market effect	1.030	1.025	1.024	1.022
Equalize commuting shares	1.028	1.021	1.022	1.019

Notes: Table plots the welfare gain for incumbents in Kinondoni (Phase 1). The equalize counterfactual in each case is making high types have the same exogenous parameters as low types.

within a city, then any such place-based investment can lead to neighborhood changes, such as rent increases, which change who can afford to live near these investments and hence who benefits from them.

We provide a method to analyze the distributional effects of neighborhood investment. We show that average welfare gains across the city as a whole, and average welfare gains by initial location, can be recovered if a researcher knows three key ex-ante facts: i) the ex-ante living and working matrix by type, ii) the ex-ante expenditure on rent by location and type, iii) ex-ante earnings in each location broken down by type and living location; and four key parameters: i) an amenity or productivity sorting parameter, ii) the proportion of income spent on rent by type, iii) the elasticity of living location to rent by type, and iv) the proportion of production income paid to land. Using original panel data we collected in Dar es Salaam, we study the distributional effects of Dar es Salaam's nascent BRT system.

Overall, we find that Phase 1 of the BRT led to an average increase in welfare of 2.4% for the city's poor, and 2.3% for the city's rich. Focusing on the original inhabitants of the neighborhood where Phase 1 was constructed, we estimate that the initial poor receive a 3.0% gain, and the initial rich receive a 2.5% gain. Both findings indicate that there are not sizeable general equilibrium effects. Consequently, the average welfare effects are largely determined by the proportion of rich and poor types that, ex-ante, travel along the proposed BRT routes. Given this, the first BRT line, which runs mostly from a relatively wealthy neighborhood to downtown has a larger welfare gain for rich than poor. Line two mostly favors the poor, and in total, with all six lines built, we predict relatively equal welfare effects.

Why are the welfare effects so similar for high and low types? This result comes from a combination of observations in the data. First, the ex-ante distribution of people across space indicates that there are not parts of Dar es Salaam that are particularly preferred by high or by low types. This then implies that “displacement” is not particularly costly. Second, while there are differences in rents expenditure across types, this difference is more than enough to explain the difference across types in elasticity of living location to rental rates. Given this, we conclude that there are no strong externalities, so an influx of high types into an area does not strongly dissuade the poor from living there. Finally, for reasonable values of the importance of human capital in production, the small changes in commute choices predicted are insufficient to have large effects on the productivities of different locations. In interpreting these results it is important to note that the model, as discussed above, is quite capable of delivering a “gentrification effect” where the (initial) poor benefit much less than the (initial) rich; it is the data the suggests that this is not a likely outcome in the city of Dar es Salaam.

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A Data collection appendix

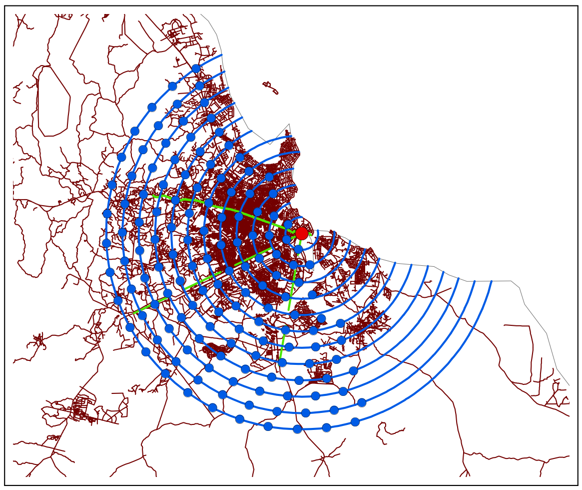
A.1 Timeline of activities

Research Activities		Operational Activities
	September 2008	Phase 1 prequalification procurement process begins
	April 2012	Construction of Phase 1 begins
	October 2015	Funds secured for Phase 2
	December 2015	Construction of Phase 1 complete
Travel time survey; baseline survey	January 2016	
	April 2016	Phase 1 begins partial operations
	May 2016	Phase 1 begins full operations
Mobile survey 1	May 2017	
Mobile survey 2	July 2017	
Midline survey; mobile survey 3	September 2017	
Mobile survey 4	November 2017	
Midline attrition survey	February 2018	
Mobile survey 5	July 2018	Bids for building Phase 2 due
Mobile survey 6	November 2018	
Endline survey	January 2019	Expected bid concession for Phase 2
	June 2019	Phase 2 construction expected start
Endline follow-up survey	September 2019	

A.2 Sample frame

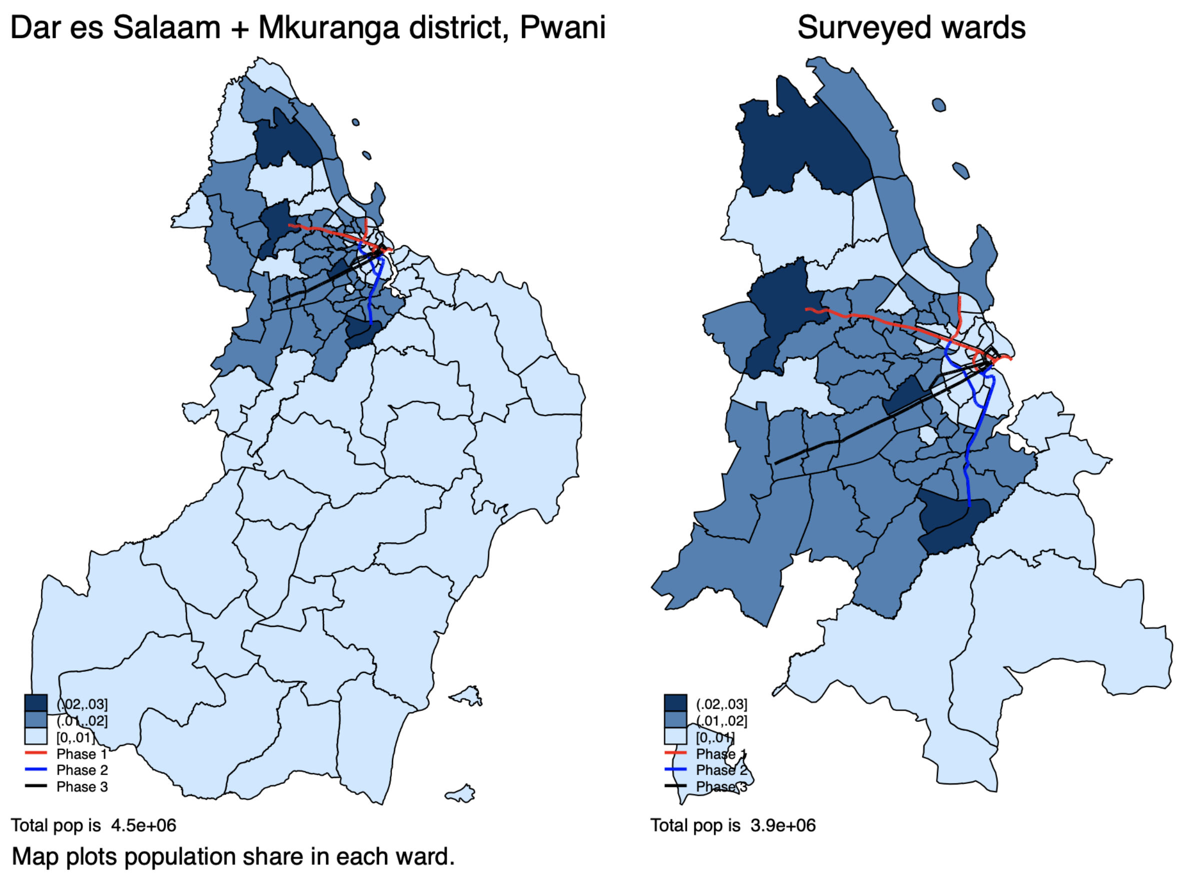
Our survey used a geographical sampling frame to cover households at locations in all directions within 18 km of the central business district of Dar es Salaam. This area encompassed wards from the region of Dar es Salaam as well as two wards from a neighboring district. Figure A1 shows the survey locations within the city of Dar es Salaam.

Appendix Figure A1: Geographical Sampling Strategy



In terms of population coverage, Figure A2 plots the population distribution from the 2012 population Census. Panel (a) of Figure A2 shows the districts of Dar es Salaam and neighboring Mkuranga district, Pwani. In the 2012 Census, this area had 4.5 million inhabitants. Panel (b) shows the wards that we surveyed. These wards accounted for 3.9 million people or 87% of the population of Dar es Salaam.

Appendix Figure A2: 2012 population census



A.3 Recontact rates between baseline and endline

Appendix Table A1: Status of full sample at endline

	(1) Ever enrolled	(2) Still in sample at endline
Structures		
Found and survey complete	67.5	75.7
Found and refused /incomplete	9.6	3.7
Not found	18.1	15.3
Torn down / empty	4.7	5.3
N	2511	2241
Households		
Found and survey complete	70.8	80.5
Found and refused/incomplete	9.4	3.6
Not found	18.4	15.9
Splitoff returned original hh / left Dar	1.4	
N	2542	2237
Male/female respondents		
Found and survey complete	73.8	83.4
Found and refused /incomplete	11.8	5.7
Not found	13.0	9.2
Died	1.5	1.7
N	3891	3441

Notes: Table shows percent in each status. We initially enrolled 1748 structures and households. Up to two individual respondents (one male, one female) were enrolled per household. We stopped tracking structures after midline if they (i) refused, or (ii) we were not able to locate either the structure or the household after exhausting all contact information available. We did not attempt to find non-tracked sample at endline.

A.4 Attrition balance

Appendix Table A2: Structure-Level Attrition balance for households enrolled at baseline

	Endline					Endline mop up	
	(1) Complete	(2) Incomplete	(3) Refused	(4) Not found	(5) Torn down/empty	(6) Surveyed	(7) Surveyed if attempted
Log BL HH monthly gross income per capita	-0.032***	0.001	0.004	0.022***	0.009	-0.027**	0.001
	(0.011)	(0.001)	(0.008)	(0.007)	(0.006)	(0.011)	(0.009)
Log BL monthly rent per room	-0.036***	-0.000	0.020**	0.007	0.005	-0.031**	-0.003
	(0.013)	(0.001)	(0.008)	(0.006)	(0.007)	(0.014)	(0.013)
BL number of years lived in the structure	0.002	-0.000*	0.001	-0.001**	-0.001	0.002*	0.000
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
BL number of HH in the structure	0.006	0.000	-0.002	-0.009*	0.002	0.010	0.005
	(0.006)	(0.001)	(0.004)	(0.005)	(0.003)	(0.006)	(0.007)
Dwelling rented by HH	-0.145***	-0.002	-0.008	0.134***	0.008	-0.119**	-0.011
	(0.053)	(0.006)	(0.025)	(0.027)	(0.026)	(0.054)	(0.044)
Dwelling owned by HH	0.101**	-0.006	-0.006	-0.051**	-0.045**	0.129**	0.051
	(0.046)	(0.006)	(0.021)	(0.022)	(0.020)	(0.050)	(0.033)
BL distance to phase 1	0.004	0.000	-0.002	0.000	-0.001	0.007*	0.004
	(0.003)	(0.000)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
BL distance to phase 2	0.004	-0.000	-0.002	-0.003	-0.001	0.003	-0.000
	(0.004)	(0.000)	(0.001)	(0.002)	(0.002)	(0.004)	(0.003)
N	1748	1748	1748	1748	1748	1748	1325
Mean dependent variable	0.760	0.002	0.069	0.082	0.058	0.648	0.855

Notes: Standard errors, clustered by aggregate spatial units, are reported in parentheses. Missing values for the independent variables are dummied out. Incomplete includes structures that were found but whose household either did not complete the survey or refused to be surveyed. Refused includes structures that were either tracked and found at EL but the household refused to be surveyed at EL or not tracked at EL because the household refused to be surveyed at ML. Not found includes structures that were tracked but not found at EL, structures we did not look for at EL because we ran out of time, or structures that were not tracked at EL because they were not found at ML. We dropped observations for structures whose households splitoff from their BL structure at ML but returned to original HH at EL and those that were not tracked because they were outside Dar.

Appendix Table A3: Household-Level Attrition balance for households enrolled at baseline

	Endline			Endline mop up	
	(1) Complete	(2) Refused	(3) Not found	(4) Surveyed	(5) Surveyed if attempted
Log BL HH monthly gross income per capita	-0.030**	0.013	0.017*	-0.036***	-0.012
	(0.012)	(0.008)	(0.008)	(0.011)	(0.009)
Log BL monthly rent per room	-0.027**	0.025**	0.002	-0.023*	-0.001
	(0.013)	(0.012)	(0.007)	(0.014)	(0.011)
BL number of years lived in the structure	0.000	0.001	-0.001	0.001	0.001
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
BL number of HH in the structure	0.010	-0.001	-0.009*	0.014**	0.008
	(0.007)	(0.004)	(0.005)	(0.007)	(0.006)
Dwelling rented by HH	-0.173***	-0.014	0.187***	-0.112**	0.049
	(0.042)	(0.020)	(0.042)	(0.047)	(0.038)
Dwelling owned by HH	0.065*	0.000	-0.066***	0.083*	0.037
	(0.034)	(0.029)	(0.019)	(0.042)	(0.033)
BL distance to phase 1	0.001	-0.002	0.002	0.004	0.004*
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
BL distance to phase 2	0.001	0.001	-0.002	0.001	0.000
	(0.003)	(0.002)	(0.002)	(0.004)	(0.002)
N	1748	1748	1748	1748	1391
Mean dependent variable	0.796	0.092	0.112	0.682	0.858

Notes: Standard errors, clustered by aggregate spatial units, are reported in parentheses. Missing values for the independent variables are dummied out. Refused includes households that were either tracked at EL but refused to be surveyed or not tracked at EL because they refused to be surveyed at ML. Not found includes households that were tracked but not found at EL, not contacted at because EL we ran out of time, or not tracked at EL because either they were not found at ML or they splitoff outside Dar at ML. We dropped households that splitoff from BL structure at ML but returned to original HH at EL.

Appendix Table A4: Individual-Level Attrition balance for households enrolled at baseline

	Endline					Endline mop up	
	(1) Complete	(2) Incomplete	(3) Refused	(4) Not found	(5) Died	(6) Surveyed	(7) Surveyed if attempted
Log BL HH monthly gross income per capita	-0.034***	0.004	0.012	0.022***	-0.004	-0.030**	-0.009
	(0.011)	(0.004)	(0.008)	(0.007)	(0.003)	(0.011)	(0.011)
Log BL monthly rent per room	-0.029**	0.002	0.024*	0.004	-0.000	-0.025**	-0.001
	(0.012)	(0.004)	(0.013)	(0.007)	(0.003)	(0.011)	(0.011)
BL number of years lived in the structure	-0.001	-0.000	0.001	0.000	0.000	-0.001	0.000
	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
BL number of HH in the structure	0.010*	-0.003**	-0.002	-0.004	-0.002	0.011**	0.009*
	(0.005)	(0.001)	(0.004)	(0.004)	(0.001)	(0.005)	(0.005)
Dwelling rented by HH	-0.143***	-0.004	-0.013	0.149***	0.012	-0.104***	0.009
	(0.033)	(0.011)	(0.020)	(0.023)	(0.010)	(0.037)	(0.039)
Dwelling owned by HH	0.033	0.017*	-0.006	-0.048**	0.004	0.056*	0.015
	(0.032)	(0.010)	(0.027)	(0.019)	(0.007)	(0.032)	(0.027)
BL distance to phase 1	0.002	-0.000	-0.003*	0.001	-0.000	0.004	0.005*
	(0.003)	(0.001)	(0.001)	(0.003)	(0.001)	(0.003)	(0.002)
BL distance to phase 2	-0.001	0.002*	0.001	-0.001	-0.001*	-0.001	-0.001
	(0.004)	(0.001)	(0.002)	(0.002)	(0.000)	(0.003)	(0.002)
BL Age	0.002	0.000	-0.000	-0.003**	0.001***	0.002**	0.000
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
Male dummy	-0.059***	0.026***	0.008	0.020*	0.005	0.002	0.032*
	(0.012)	(0.007)	(0.007)	(0.011)	(0.005)	(0.014)	(0.016)
N	3104	3104	3104	3104	3104	3104	2325
Mean dependent variable	0.697	0.034	0.100	0.151	0.018	0.589	0.786

Notes: Standard errors, clustered by aggregate spatial units, are reported in parentheses. Missing values for the independent variables are dummied out. Refused includes male/female respondents that were tracked at EL but refused to be surveyed and those that were not tracked at EL because either the household or male/female respondent refused at ML. Not found includes male/female respondents that were tracked but not found at EL and those that were not tracked at EL because the household was not found at ML.

B Data appendix

B.1 Trimming

To reduce the influence of outliers outcome variables are trimmed to exclude the top 1% of observations before analysis.

B.2 Rent

Two rent variables were collected during all survey rounds: actual monthly rent (answered only by those households paying rent) and expected monthly rent (answered by all households, including households that owned their structure or lived in them without paying rent).[25]

Endline surveying revealed some inconsistencies in the way in which respondents accounted for the number of rooms in their property in answering rental questions. We clarified these inconsistencies with a series of detailed follow-up questions and checks relating to the rental variable questions during a follow-up call center conducted in September-October 2019. The final rent variables, therefore, reflect observations for the 83% of baseline households that were surveyed at the endline and were reached during the follow-up call center. Structure characteristics are balanced across households that were and were not reached during the follow-up call center.

[25] Expected monthly rent was obtained as the answer to the survey question "Assume you want to rent the rooms of this dwelling that are occupied by your household (with no equipment). What would be a real monthly rent for each room?"

Appendix Table A5: Endline Follow-Up Phone Survey Attrition Balance

	Contacted during follow-up b/se/p
Change rent expected per room	-0.000
	(0.000)
	[0.988]
Time to Kariakoo	0.000
	(0.000)
	[0.192]
Rooms household occupies	0.016***
	(0.006)
	[0.005]
Number of households in structure	0.005
	(0.005)
	[0.294]
Distance to Phase 1 (km)	0.000
	(0.002)
	[0.864]
Categorical moved variable	0.011
	(0.007)
	[0.111]
Constant	0.751***
	(0.045)
	[0.000]

Notes: Robust standard errors are reported in parentheses.

B.3 Location of residence and employment

At both baseline and endline, GPS coordinates were recorded at all structures visited in person, provided the respondents gave consent. Region, district, and ward identifiers for structures surveyed are based on matching the recorded GPS coordinates to shapefiles of the administrative divisions in our study area.

During the follow-up call center in September-October 2019, respondents were asked to self-report the ward in which they work and retrospective information on the same variable at the time of baseline surveying.[26]

B.4 Pretrend analysis

Appendix Table A6: Log rent prrm (exp): Household-Level

	(1) WB v. BL	(2) BL v. EL	(3) WB v. BL	(4) BL v. EL
Post	0.184	-0.259	0.172	-0.249
	0.131	0.107**	0.129	0.103**
$<$2 km from Ph 1	0.302	0.105	-0.107	-0.523
	0.120**	0.121	0.121	0.122***
$<$2 km from Ph 1 $\times$ Post	-0.197	0.348	-0.246	0.334
	0.153	0.159**	0.186	0.173*
N	895	723	895	721
spatial unit FE			✓	✓
weighted	✓	✓	✓	✓

Notes: Unit of observation is household by year. Standard errors clustered at aggregate spatial unit. Sample is structures within 2 km of either Phase 1 or Phase 3.

[26]The survey question was asked according to the respondent's employment classification; for example, traders were asked where they sell their goods while non-traders were asked where they usually carry out their main job."

Appendix Table A7: High type: Household-Level

	(1) WB v. BL	(2) BL v. EL	(3) WB v. BL	(4) BL v. EL
Post	0.062	-0.052	0.017	-0.050
	0.067	0.037	0.049	0.040
$<$2 km from Ph 1	0.187	0.215	-0.025	-0.607
	0.049***	0.091**	0.097	0.043***
$<$2 km from Ph 1 $\times$ Post	0.028	0.030	0.016	0.033
	0.087	0.053	0.071	0.053
N	1125	812	1125	810
spatial unit FE			✓	✓
weighted	✓	✓	✓	✓

Notes: Unit of observation is household by year. Standard errors clustered at aggregate spatial unit. Sample is structures within 2 km of either Phase 1 or Phase 3.

C Derivation of initial exact hat

This section derives (i) the probability that an individual who initially chose to go to location o switches to location d, and (ii) the value of the productivity shock in d given that that initially chose to go to location o and then switched in location d.

C.1 Derivation of migration probability

C.1.1 Case 1: $d \neq o$

$$P(w_1\epsilon_1 < t)...P(w_d\epsilon_d < t)....P(w_o\epsilon_o = t)...P(w_N\epsilon_N = t) \tag{22}$$

$$P(\tilde{w}_1\epsilon_1 < \tilde{t})....P(\tilde{w}_d\epsilon_d = \tilde{t})....P(\tilde{w}_o\epsilon_o < \tilde{t})...P(\tilde{w}_N\epsilon_N < \tilde{t}) \tag{23}$$

Substituting in the inequalities, this implies:

$$\epsilon_1 < \min[\frac{t}{w_1}, \frac{\tilde{t}}{\tilde{w}_1}], ..., (w_d\frac{\tilde{t}}{\tilde{w}_d} < t), ..., (\tilde{w}_o\frac{t}{w_o} < \tilde{t}), ..., \epsilon_N < \min[\frac{t}{w_N}, \frac{\tilde{t}}{\tilde{w}_N}] \tag{24}$$

We make, WLOG, the ordering assumption that $\hat{w}_1 > \hat{w}_2 > ... > \hat{w}_{N-1} > \hat{w}_N$. This implies the following inequalities:

$$t \in [\hat{w}_d^{-1}\tilde{t}, \hat{w}_o^{-1}\tilde{t}] \tag{25}$$

$$\frac{t}{w_1} < \frac{\tilde{t}}{\tilde{w}_1} \rightarrow t < \hat{w}_1^{-1}\tilde{t} \qquad \text{Never true in the interval} \tag{26}$$

$$... \tag{27}$$

$$\frac{t}{w_{d-1}} < \frac{\tilde{t}}{\tilde{w}_{d-1}} \rightarrow t < \hat{w}_{d-1}^{-1}\tilde{t} \qquad \text{Never true in the interval} \tag{28}$$

$$... \tag{29}$$

$$\frac{t}{w_{d+1}} < \frac{\tilde{t}}{\tilde{w}_{d+1}} \rightarrow t < \hat{w}_{d+1}^{-1}\tilde{t} \qquad \text{Flips in the interval} \tag{30}$$

$$... \tag{31}$$

$$d\frac{t}{w_{o-1}} < \frac{\tilde{t}}{\tilde{w}_{o-1}} \rightarrow t < \hat{w}_{o-1}^{-1}\tilde{t} \qquad \text{Flips in the interval} \tag{32}$$

$$... \tag{33}$$

$$\frac{t}{w_{o+1}} < \frac{\tilde{t}}{\tilde{w}_{o+1}} \rightarrow t < \hat{w}_{o+1}^{-1}\tilde{t} \qquad \text{Always true in the interval} \tag{34}$$

$$... \tag{35}$$

$$\frac{t}{w_N} < \frac{\tilde{t}}{\tilde{w}_N} \rightarrow t < \hat{w}_N^{-1}\tilde{t} \qquad \text{Always true in the interval} \tag{36}$$

So the integral we need to solve is:

$$\begin{aligned}
\pi_{od} = &\int_{\tilde{t}=0}^{\tilde{t}=\infty} \int_{t=\hat{w}_d^{-1}\tilde{t}}^{t=\hat{w}_{d+1}^{-1}\tilde{t}} F_{\epsilon_{d+1}}(\frac{t}{w_{d+1}})...F_{\epsilon_{o-1}}(\frac{t}{w_{o-1}})F_{\epsilon_{o+1}}(\frac{t}{w_{o+1}})...F_{\epsilon_N}(\frac{t}{w_N})f_{\epsilon_o}(\frac{t}{w_o})dtF_{\epsilon_1}(\frac{\tilde{t}}{\tilde{w}_1})F_{\epsilon_2}(\frac{\tilde{t}}{\tilde{w}_1})...F_{\epsilon_d} \\
+ &\int_{\tilde{t}=0}^{\tilde{t}=\infty} \int_{t=\hat{w}_{d+1}^{-1}\tilde{t}}^{t=\hat{w}_{d+2}^{-1}\tilde{t}} F_{\epsilon_{d+2}}(\frac{t}{w_{d+2}})...F_{\epsilon_{o-1}}(\frac{t}{w_{o-1}})F_{\epsilon_{o+1}}(\frac{t}{w_{o+1}})...F_{\epsilon_N}(\frac{t}{w_N})f_{\epsilon_o}(\frac{t}{w_o})dtF_{\epsilon_1}(\frac{\tilde{t}}{\tilde{w}_1})F_{\epsilon_2}(\frac{\tilde{t}}{\tilde{w}_1})...F_{\epsilon_{d-1}}(\frac{\tilde{t}}{\tilde{w}_d} \\
&+ ... \\
+ &\int_{\tilde{t}=0}^{\tilde{t}=\infty} \int_{t=\hat{w}_{o-1}^{-1}\tilde{t}}^{t=\hat{w}_o^{-1}\tilde{t}} F_{\epsilon_{o+1}}(\frac{t}{w_{o+1}})...F_{\epsilon_N}(\frac{t}{w_N})f_{\epsilon_o}(\frac{t}{w_o})dtF_{\epsilon_1}(\frac{\tilde{t}}{\tilde{w}_1})F_{\epsilon_2}(\frac{\tilde{t}}{\tilde{w}_1})...F_{\epsilon_{d-1}}(\frac{\tilde{t}}{\tilde{w}_{d-1}})F_{\epsilon_{d+1}}(\frac{\tilde{t}}{\tilde{w}_{d+1}})F_{\epsilon_{d+2}}(\frac{\tilde{t}}{\tilde{w}_{d+2}}
\end{aligned} \tag{37}$$

When we solve this, we get:

$$
\begin{aligned}
\pi_{od} = & \left(\frac{w_o^\alpha}{w_{d+1}^\alpha + w_{d+2}^\alpha + \ldots + w_N^\alpha}\right) \left[\left(\frac{w_d^\alpha}{\bar{w}_1^\alpha + \bar{w}_2^\alpha + \ldots + \bar{w}_d^\alpha + (w_{d+1}^\alpha + \ldots + w_N^\alpha)\hat{w}_{d+1}^\alpha} \right) - \left(\frac{}{\bar{w}_1^\alpha + \bar{w}_2^\alpha + \ldots} \right. \right. \\
& + \left(\frac{w_o^\alpha}{w_{d+2}^\alpha + \ldots + w_N^\alpha}\right) \left[\left(\frac{w_d^\alpha}{\bar{w}_1^\alpha + \bar{w}_2^\alpha + \ldots + \bar{w}_d^\alpha + \bar{w}_{d+1}^\alpha + (w_{d+2}^\alpha + \ldots + w_N^\alpha)\hat{w}_{d+1}^\alpha} \right) - \left(\frac{}{\bar{w}_1^\alpha + \bar{w}_2^\alpha + \ldots + \bar{w}} \right. \right. \\
& + \ldots \\
& + \left(\frac{w_o^\alpha}{w_o^\alpha + w_{o+1}^\alpha + \ldots + w_N^\alpha}\right) \left[\left(\frac{w_d^\alpha}{\bar{w}_1^\alpha + \bar{w}_2^\alpha + \ldots + \bar{w}_d^\alpha + \bar{w}_{d+1}^\alpha + \ldots + \bar{w}_{o-1}^\alpha + (w_o^\alpha + \ldots + w_N^\alpha)\hat{w}_o^\alpha} \right) - \left(\frac{}{\bar{w}_1^\alpha} \right. \right.
\end{aligned}
\tag{38}
$$

Generalizing this formula, we have:

$$
\pi_{od} = \sum_{j=d}^{j=o-1} \left(\frac{w_o^\alpha}{\sum_{i=j+1}^{i=N} w_i^\alpha} \right) \left[\frac{\tilde{w}_d^\alpha}{\sum_{i=1}^{i=j} \tilde{w}_i^\alpha + (\sum_{i=j+1}^{i=N} w_i^\alpha)\hat{w}_{j+1}^\alpha} - \frac{\tilde{w}_d^\alpha}{\sum_{i=1}^{i=j} \tilde{w}_i^\alpha + (\sum_{i=j+1}^{i=N} w_i^\alpha)\hat{w}_j^\alpha} \right] \tag{39}
$$

C.1.2 Case 2: $d = o$

Note this formula doesn't work for the case where $d = o$ i.e., you stay in the same location. The working for that case is:

$$
P(w_1\epsilon_1 < t) \ldots P(w_o\epsilon_o = t) \ldots P(w_N\epsilon_N = t) \tag{40}
$$

$$
P(\tilde{w}_1\epsilon_1 < \tilde{t}) \ldots P(\tilde{w}_o\epsilon_o = \tilde{t}) \ldots P(\tilde{w}_N\epsilon_N = \tilde{t}) \tag{41}
$$

Substituting in the inequalities, this implies:

$$
\epsilon_1 < \min[\frac{t}{w_1}, \frac{\tilde{t}}{\tilde{w}_1}], \ldots, w_o\frac{\tilde{t}}{\tilde{w}_o} = t, \ldots, \epsilon_N < \min[\frac{t}{w_N}, \frac{\tilde{t}}{\tilde{w}_N}] \tag{42}
$$

This implies the following inequalities:

$$t = w_o^{-1}\tilde{t} \tag{43}$$

$$\frac{t}{w_1} < \frac{\tilde{t}}{\tilde{w}_1} \rightarrow t < \hat{w}_1^{-1}\tilde{t} \qquad \text{Never true in the interval} \tag{44}$$

$$... \tag{45}$$

$$\frac{t}{w_{o-1}} < \frac{\tilde{t}}{\tilde{w}_{o-1}} \rightarrow t < \hat{w}_{o-1}^{-1}\tilde{t} \qquad \text{Never true in the interval} \tag{46}$$

$$... \tag{47}$$

$$\frac{t}{w_{o+1}} < \frac{\tilde{t}}{\tilde{w}_{o+1}} \rightarrow t < \hat{w}_{o+1}^{-1}\tilde{t} \qquad \text{Always true in the interval} \tag{48}$$

$$... \tag{49}$$

$$\frac{t}{w_N} < \frac{\tilde{t}}{\tilde{w}_N} \rightarrow t < \hat{w}_N^{-1}\tilde{t} \qquad \text{Always true in the interval} \tag{50}$$

So the integral is:

$$\pi_{oo} = \int_{\tilde{t}=0}^{\tilde{t}=\infty} F_{\epsilon_1}\left(\frac{\tilde{t}}{\tilde{w}_1}\right) ...F_{\epsilon_{o-1}}\left(\frac{\tilde{t}}{\tilde{w}_{o-1}}\right) F_{\epsilon_{o+1}}\left(\frac{t}{w_{o+1}}\right) ...F_{\epsilon_N}\left(\frac{t}{w_N}\right) f_{\epsilon_o}\left(\frac{\tilde{t}}{\tilde{w}_o}\right) d\tilde{t} \tag{51}$$

$$= \int_{\tilde{t}=0}^{\tilde{t}=\infty} F_{\epsilon_1}\left(\frac{\tilde{t}}{\tilde{w}_1}\right) ...F_{\epsilon_{o-1}}\left(\frac{\tilde{t}}{\tilde{w}_{o-1}}\right) F_{\epsilon_{o+1}}\left(\frac{\hat{w}_o^{-1}\tilde{t}}{w_{o+1}}\right) ...F_{\epsilon_N}\left(\frac{\hat{w}_o^{-1}\tilde{t}}{w_N}\right) f_{\epsilon_o}\left(\frac{\tilde{t}}{\tilde{w}_o}\right) d\tilde{t} \tag{52}$$

$$= \int_{\tilde{t}=0}^{\tilde{t}=\infty} \tilde{w}_o^{\alpha}\alpha\tilde{t}^{-(\alpha+1)} \exp^{-(\sum_{i=1}^{i=o}\tilde{w}_i^{\alpha}+\left(\sum_{i=o+1}^{i=N}w_i^{\alpha}\right)\hat{w}_o^{\alpha})\tilde{t}^{-\alpha}} d\tilde{t} \tag{53}$$

$$= \frac{\tilde{w}_o^{\alpha}}{\sum_{i=1}^{i=o}\tilde{w}_i^{\alpha} + \left(\sum_{i=o+1}^{i=N} w_i^{\alpha}\right)\hat{w}_o^{\alpha}} \tag{54}$$

C.2 Derivation of idiosyncratic shock

We want to derive $E(\epsilon_d|\text{choose } o \text{ then choose } d)$. To proceed, note that above we assume $\tilde{w}_d\epsilon_d = \tilde{t}$. So, we solve for $E(\tilde{t}|\text{choose } o \text{ then choose } d)$ and then solve for $E(\epsilon_d|\text{choose } o \text{ then choose } d) = \frac{E(\epsilon_d|\text{choose } o \text{ then choose } d).}{\tilde{w}_d}$.

C.2.1 Case 1: $d \neq o$

** NEED TO ADD WORKING **

C.2.2 Case 2: $d = o$

And we want to find $E(\tilde{t}|\text{go to o and stay in o})$:

$$
\begin{aligned}
E(\tilde{t}|oo) &= \frac{1}{\pi_{oo}} \int_{\tilde{t}=0}^{\tilde{t}=\infty} \tilde{w}_o^\alpha \alpha \tilde{t}^{-(\alpha+1)} \exp^{-(\sum_{i=1}^{i=o} \tilde{w}_i^\alpha + (\sum_{i=o+1}^{i=N} w_i^\alpha) \hat{w}_o^\alpha) \tilde{t}^{-\alpha}} \tilde{t} d\tilde{t} && (55) \\
&= \left[\sum_{i=1}^{i=o} \tilde{w}_i^\alpha + \left(\sum_{i=o+1}^{i=N} w_i^\alpha \right) \hat{w}_o^\alpha \right]^{\frac{1}{\alpha}} \Gamma \left(1 - \frac{1}{\alpha} \right) && (56) \\
E(\epsilon_o|\text{choose oo}) &= \frac{E(\tilde{t}|\text{choose oo})}{\tilde{w}_o} && (57) \\
&= \frac{\left[\sum_{i=1}^{i=o} \tilde{w}_i^\alpha + \left(\sum_{i=o+1}^{i=N} w_i^\alpha \right) \hat{w}_o^\alpha \right]^{\frac{1}{\alpha}}}{\tilde{w}_o} \Gamma \left(1 - \frac{1}{\alpha} \right) && (58) \\
&= \frac{\left[\sum_{i=1}^{i=o} \tilde{w}_i^\alpha + \left(\sum_{i=o+1}^{i=N} w_i^\alpha \right) \hat{w}_o^\alpha \right]^{\frac{1}{\alpha}}}{(\tilde{w}_o^\alpha)^{\frac{1}{\alpha}}} \Gamma \left(1 - \frac{1}{\alpha} \right) && (59) \\
&= \pi_{oo}^{\frac{-1}{\alpha}} \Gamma \left(1 - \frac{1}{\alpha} \right) && (60)
\end{aligned}
$$

C.3 Combined formula

Note, we have an ordering assumption that $\hat{w}_1 > \hat{w}_2 > ... > \hat{w}_N$. It will never be optional to migrate to a place with a lower increase in wage than where you currently are. The final formula are:

$$
P(\text{chose o then d}) = \pi_{od} = \begin{cases} 0, \text{if } d > o \\ \frac{\tilde{w}_o^\alpha}{\sum_{i=1}^{i=o} \tilde{w}_i^\alpha + (\sum_{i=o+1}^{i=N} w_i^\alpha) \hat{w}_o^\alpha}, \text{if } d{=}o \\ \sum_{j=d}^{j=o-1} \left(\frac{w_o^\alpha}{\sum_{i=j+1}^{i=N} w_i^\alpha} \right) \left[\frac{\tilde{w}_d^\alpha}{\sum_{i=1}^{i=j} \tilde{w}_i^\alpha + (\sum_{i=j+1}^{i=N} w_i^\alpha) \hat{w}_{j+1}^\alpha} - \frac{\tilde{w}_d^\alpha}{\sum_{i=1}^{i=j} \tilde{w}_i^\alpha + (\sum_{i=j+1}^{i=N} w_i^\alpha) \hat{w}_j^\alpha} \right], \text{otherw} \end{cases} \quad (61)
$$

$$E(\epsilon_d|\text{choose o then d}) = \epsilon_{od} = \begin{cases} 0, \text{if } d > o \\ \frac{1}{\pi_{oo}} \left[\frac{\tilde{w}_o^\alpha}{\sum_{i=1}^{i=o} \tilde{w}_i^\alpha + \left(\sum_{i=o+1}^{i=N} w_i^\alpha\right) \hat{w}_o^\alpha} \right]^{\frac{\alpha-1}{\alpha}}, \text{if } d = o \\ \frac{1}{\pi_{od}} \sum_{j=d}^{j=o-1} \left(\frac{w_o^\alpha}{\sum_{i=j+1}^{i=N} w_i^\alpha} \right) \left[\left(\frac{\tilde{w}_d^\alpha}{\sum_{i=1}^{i=j} \tilde{w}_i^\alpha + (\sum_{i=j+1}^{i=N} w_i^\alpha) \hat{w}_{j+1}^\alpha} \right)^{\frac{\alpha-1}{\alpha}} - \left(\frac{\tilde{w}_d^\alpha}{\sum_{i=1}^{i=j} \tilde{w}_i^\alpha + (\sum_{i=j+1}^{i=N} \right. \right. \right. \end{cases} \tag{62}$$

C.4 Exact hat by origin

** NEED TO ADD IN WORKING **

D Structural estimation

The structural estimation uses data at the level of 52 spatial units across our study area on rent, commute shares, and income. The 52 spatial units are based on the 92 wards that are within the Dar es Salaam region or within 1km of a survey cluster; these wards are aggregated as necessary to ensure non-zero observations in all units. The spatial units are constructed by first taking the 77 wards in Tanzania that are within 1km of a survey cluster. Wards without survey clusters are aggregated with the closest ward that contains a survey cluster; this is done by finding the ward containing a survey cluster that is closest to the centroid of each ward that does not contain a survey cluster. Sandali and Vingunguti wards are also aggregated due to the long convex hull of the survey cluster contained. Finally, for the 15 wards in Dar es Salaam that are further than 1km from a survey cluster, each ward is aggregated with the spatial unit closest to its centroid.

Rent: The expected monthly rent variable (described above) was collapsed to give rent per room by ward of residence.

Commute share matrices: For both the sample of all commuters and the sample of employed commuters, reported commuting flows are collapsed by the spatial unit of residence and spatial unit of employment to yield the number of people commuting between each of these units. These flows are expressed as a share of the total population, such that shares across all origin-destination pairs add to one in each survey round. The structural estimation cannot accommodate zeros, so zero values are replaced with a small value (1e-5), and the matrices rescaled to ensure that they continue to add to one in each survey round.

Income: Gross monthly household income per capita is collapsed by ward of residence and again by origin-destination pair. If two respondents in a household both report household income, the value used is the average of the two responses.

For the exact hat estimation, we collapse the 52 spatial units to five geographical regions. These are constructed by dividing the spatial units according to whether they lie in the districts of Kinondoni, Temeke, or Ilala.[27] Separate regions are then created for the central business district (those spatial units within 3km of Kariakoo market) and outskirts (those spatial units further out than 15km from Kariakoo market).

[27] A district is a higher-level administrative subdivision than a ward in Tanzania.

E Additional tables

Appendix Table A8: Correlation in the change in Phase 1 traveltime with other phases

Change in instrument: Phase 1	(1) b/se	(2) b/se	(3) b/se	(4) b/se	(5) b/se
Change in instrument: Phase 2	0.100				
	0.035***				
Change in instrument: Phase 3		-0.066			
		0.018***			
Change in instrument: Phase 4			0.185		
			0.115		
Change in instrument: Phase 5				-0.027	
				0.026	
Change in instrument: Phase 6					0.254
					0.061***
N	2652	2652	2652	2652	2652

Notes: The table shows the correlation between the change in Phase 1 travel time and other Phases. An observation is the change in the traveltime from a ward (n=52) to every other ward; total sample size is thus 52*51=2652. Standard errors are clustered at the ward.

Appendix Table A9: did table: paper (type defined by WB 5.50 poverty line current)

	Log expected rent prrm		Log residualized expected rent prrm		High types		Live in house < 3 yrs	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	-0.267	-0.236	-0.395	-0.383	0.136	0.148	0.171	0.032
	0.108**	0.158	0.086***	0.149**	0.048***	0.055**	0.051***	0.052
< 2 km from Ph 1	0.103		-0.018		0.257		-0.043	
	0.122		0.094		0.097**		0.065	
Post $\times$ < 2 km from Ph 1	0.356	0.350	0.408	0.357	-0.229	-0.266	0.010	0.012
	0.160**	0.206	0.157**	0.199*	0.078***	0.079***	0.066	0.068
N	723	518	723	518	720	510	838	730
structID		✓		✓		✓		✓
wgt	✓	✓	✓	✓	✓	✓	✓	✓

Notes: High type is current above WB 5.50 poverty line based on expenditure (incl. imputed rent) per capita. Unit of observation is a structure by year. Sample is structures within 2 km of either Phase 1 or Phase 3. Standard errors clustered by ward (n=52).

Appendix Table A10: triplediff table: paper (type defined by WB 5.50 poverty line current)

	Log expected rent prrm		Log residualized expected rent prrm		Live in house $<$ 3 yrs	
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.212	-0.111	-0.366	-0.307	-0.013	0.006
	0.118*	0.223	0.098***	0.189	0.023	0.056
$<$ 2 km from Ph 1	0.052		-0.009		-0.116	
	0.098		0.069		0.069	
Post $\times$ $<$ 2 km from Ph 1	0.134	-0.037	0.167	-0.009	0.103	-0.125
	0.176	0.285	0.136	0.241	0.080	0.095
High type	0.428	0.339	0.319	0.328	-0.222	-0.020
	0.119***	0.272	0.102***	0.253	0.079***	0.147
Post $\times$ High type	-0.249	-0.381	-0.156	-0.273	0.287	0.022
	0.171	0.352	0.161	0.311	0.082***	0.176
$<$ 2 km from Ph 1 $\times$ High type	-0.096	-0.108	-0.152	-0.215	0.237	-0.057
	0.152	0.306	0.176	0.286	0.096**	0.176
Post $\times$ $<$ 2 km from Ph 1 $\times$ High type	0.699	1.104	0.672	1.008	-0.040	0.115
	0.327**	0.483**	0.302**	0.440**	0.132	0.202
N	709	498	709	498	720	510
structID		✓		✓		✓
wgt	✓	✓	✓	✓	✓	✓

Notes: High type is current above WB 5.50 poverty line based on expenditure (incl. imputed rent) per capita. Unit of observation is a structure by year. Sample is structures within 2 km of either Phase 1 or Phase 3. Standard errors clustered by ward (n=52).

Appendix Table A11: Estimation of commuting parameters (Interaction effects) (type defined by WB 5.50 poverty line hybrid)

	First-stage Dep var: log actual travel time	Commuting gravity Dep. var: log commuting share			Wage gravity Dep. var: log wage
	(1)	(2)	(3)	(4)	(5)
Log traveltime instrument (Phase 1)	0.497		-0.346		
	0.077***		0.119***		
High type × Log traveltime instrument (Phase 1)	0.019		0.063		
	0.007**		0.010***		
Log actual travel time		-0.207		-0.862	
		0.037***		0.272***	
High type × Log actual travel time		0.103		0.160	
		0.026***		0.031***	
Log commuting share					-0.162
					0.050***
High type × Log commuting share					-0.067
					0.011***
F stat	29.868				
N	895	1076	1033	895	838
Estimator	FS	OLS	OLS	2SLS	OLS
origxyr	✓	✓	✓	✓	✓
destxyr	✓	✓	✓	✓	✓
origxdest	✓	✓	✓	✓	✓
theta_l					6.186
theta_h					4.381
thetaeps_l				1.159	
thetaeps_h				1.423	
impliedeps_l				0.187	
impliedeps_h				0.325	

Notes: High type is hybrid above WB 5.50 poverty line based on expenditure (incl. imputed rent) per capita. Sample is commuting choices between 52 origins and 52 destinations. Orig-yr and dest-yr fixed effects computed at the 52 level. Pair fixed effects computed at the 5 level. Predicted travel time is populated for all pairs. Actual travel time comes from the survey data and is only populated for pairs with positive flows. Sample is all. Standard errors clustered at the pair level.

Appendix Table A12: Robustness: Hedonic rent regressions (bl mu) (type defined by WB 5.50 poverty line hybrid)

	Expected rent			Paid rent		
	(1)	(2)	(3)	(4)	(5)	(6)
Dep var: log rent per room						
Electricity in house for lighting	0.372	0.305		0.420	0.271	
	0.030***	0.032***		0.041***	0.041***	
Street has lights	-0.076	0.029		-0.052	0.201	
	0.056	0.060		0.070	0.076***	
Road is paved	0.111	0.137		0.143	0.185	
	0.034***	0.036***		0.048***	0.049***	
HH uses non-latrine toilet	0.179	0.202		0.144	0.136	
	0.028***	0.029***		0.037***	0.036***	
HH has piped water	0.083	-0.003		0.131	0.073	
	0.026***	0.027		0.036***	0.036**	
HH has non-wood cooking	0.334	0.291		0.315	0.234	
	0.033***	0.034***		0.044***	0.043***	
HH has cement walls	0.130	0.157		0.095	0.077	
	0.066**	0.068**		0.104	0.098	
HH has slate roof	0.505	0.486		-0.092	-0.020	
	0.181***	0.176***		0.247	0.224	
High type	0.331	0.248	0.344	0.262	0.145	0.180
	0.027***	0.028***	0.029***	0.036***	0.037***	0.039***
HH owns building	-0.028	0.030		0.000	0.000	
	0.026	0.026		.	.	
N	3277	3277	3277	858	858	858
N struc	2075	2075	2075	688	688	688
locFE	X	✓	✓	X	✓	✓
strucFE	X	X	X	X	X	X
yrFE	✓	✓	✓	✓	✓	✓

Notes: High type is hybrid above WB 5.50 poverty line based on expenditure (incl. imputed rent) per capita. Regression weighted by hh weight.

Appendix Table A13: Robustness: Share of total expenditures (type defined by WB 5.50 poverty line hybrid), post is 0

	By type		By ownership status		By type if renter		By type if renter (reported expenditure rent)	
	(1) Low type	(2) High type	(3) Non-owner	(4) Owner	(5) Low type	(6) High type	(7) Low type	(8) High type
Food	0.49	0.41	0.49	0.40	0.52	0.45	0.52	0.46
	(0.16)	(0.16)	(0.17)	(0.15)	(0.16)	(0.17)	(0.16)	(0.17)
Utilities	0.08	0.08	0.08	0.07	0.08	0.08	0.08	0.08
	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)	(0.06)
School	0.04	0.05	0.04	0.06	0.03	0.05	0.03	0.05
	(0.06)	(0.10)	(0.08)	(0.08)	(0.05)	(0.11)	(0.05)	(0.10)
Transit	0.10	0.10	0.10	0.10	0.11	0.10	0.11	0.10
	(0.07)	(0.08)	(0.08)	(0.07)	(0.08)	(0.09)	(0.08)	(0.08)
Health	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Clothing	0.08	0.09	0.09	0.07	0.09	0.10	0.09	0.10
	(0.09)	(0.08)	(0.09)	(0.08)	(0.09)	(0.08)	(0.09)	(0.08)
Other	0.01	0.02	0.02	0.02	0.02	0.02	0.02	0.02
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
(Imputed) rent	0.15	0.19	0.13	0.24	0.12	0.14		
	(0.12)	(0.16)	(0.12)	(0.16)	(0.09)	(0.14)		
Reported rent							0.12	0.13
							(0.09)	(0.10)
N	990	731	604	1117	347	257	347	257
Mean monthly per capita (implied) expenditure	109,674	286,419	190,818	183,986	111,553	289,045		

Notes: High type is hybrid above WB 5.50 poverty line based on expenditure (incl. imputed rent) per capita. The unit of analysis is the household (expenditure values are simple averages of the expenditure amounts reported by all individual respondents in the household). The denominator includes imputed rent. Statistics weighted by computed sample weights.

Appendix Table A14: Household level expenditure shares across countries

	Colombia (2010)		Kenya (2005-6)		Tanzania (2007)		Uganda (2009)		United States (2010)	
	(1) Below median	(2) Above median	(3) Below median	(4) Above median	(5) Below median	(6) Above median	(7) Below median	(8) Above median	(9) Below median	(10) Above median
All										
Food	0.36	0.26	0.52	0.39	0.27	0.15	0.46	0.40	0.18	0.12
Housing	0.26	0.22	0.11	0.14	0.54	0.68	0.19	0.19	0.26	0.19
Transport	0.10	0.10	0.04	0.08	0.04	0.04	0.07	0.09	0.11	0.12
Other	0.28	0.41	0.32	0.39	0.15	0.13	0.28	0.32	0.45	0.57
Share owner-occupied	0.38	0.57	0.19	0.14	0.37	0.42	0.33	0.38	0.59	0.78
Share renting	0.53	0.35	0.74	0.77	0.54	0.50	0.61	0.44	0.38	0.21
GDP per capita (2019 USD)	6,292.49	6,292.49	448.93	448.93	283.43	283.43	758.86	758.86	41,435.29	41,435.29
Total expenditure per capita per day (2019 USD)	5.18	25.65	0.60	2.82	0.09	0.39	1.26	4.00	13.47	47.57
N	572	559	2455	2159	1632	1842	100	88	4491	2287
Renters										
Food	0.38	0.30	0.52	0.41	0.26	0.18	0.48	0.44	0.21	0.15
Housing	0.25	0.18	0.11	0.13	0.53	0.61	0.16	0.14	0.32	0.26
Transport	0.10	0.10	0.04	0.08	0.05	0.05	0.09	0.10	0.12	0.14
Other	0.27	0.41	0.32	0.39	0.16	0.16	0.27	0.31	0.36	0.45
Share owner-occupied	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Share renting	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
N	297	193	1483	1515	950	910	54	37	1760	516

Notes: Table shows the share of per capita expenditure by expenditure category. Housing category does not include housing expenditures other than rent for renters and imputed rent for owners. Data source (with sample size): Colombia National Quality of Life Survey 2010 (14,799 households), Kenya Integrated Household Budget Survey 2005 (13,154 households), Tanzania Household Budget Survey 2007 (10,466 households), Uganda National Household Survey 2009 (6,775 households), and the U.S. BLS Consumer Expenditure Surveys 2010 (7,198 households). The table was made using only urban observations.