When distance drives destination, towns can stimulate development *

Joachim De Weerdt † Luc Christiaensen ‡ Ravi Kanbur §

October 2019

Abstract

Tanzanian census and survey data show a clear gradient of rising living standards from rural areas, over small towns to big cities. That gradient also exists for the outcomes of new migrants arriving from rural areas, raising the question of why some move to seemingly sub-optimal locations. We find that a simple extension of the basic Todaro-model in which costs of moving increase with distance can align the stylized facts with the model. Using data on about 2,000 internal migrants in Tanzania we show how distance dwarfs expected income as a determinant of destination choice. We interpret these findings in the context of the rise of the small town. Like in most African countries small towns are emerging across Tanzania. We conjecture that the birth and rise of these small towns greases the wheels of the structural transformation process by lowering the distance between rural and urban areas.

*We thank Kalle Hirvonen for useful comments and Economic Development Initiatives (EDI), the Tanzanian National Bureau of Statistics (NBS) and the Organisation for Economic Co-operation and Development (OECD) for making the underlying data publically available. We acknowledge funding from Excellence of Science (EOS) Research Project 30784531 at the Research Foundation – Flanders (FWO).

†IOB, University of Antwerp & LICOS, KU Leuven. E-mail joachim.deweerdt@uantwerp.be
‡The World Bank. E-mail lchristiaensen@worldbank.org
§Cornell University. Email sk145@cornell.edu

1 Introduction

Migration is an important avenue for growth and poverty reduction, affecting both those who move (McKenzie et al. 2010, Beegle et al. 2011, Bryan et al. 2014) and those who remain (Giles and Yoo 2007, Morten 2015, Kinnan et al. 2016, De Weerdt and Hirvonen 2016). In Tanzania, the country we study in this paper, wealth is unequally spread geographically and increases with population density, just as in most of the developing world (Young, 2013; Gollin et al., 2017; Ferre et al. 2012). But while moves to densely populated cities are, on average, much more lucrative, survey data show that few people make them and many more migrants end up with more modest income gains realised through moves to smaller towns (Christiaensen et al., 2019). A key question is therefore how migrants choose their destinations: why do migrants move to seemingly sub-optimal locations?

One consideration is that there are perhaps a number of non-monetary amenities, such as health, public goods, crime or pollution that serve to compensate for the lower consumption levels. Gollin et al. (2017) argue against this possibility by showing that in 20 developing countries (including Tanzania) and across a range of non-monetary amenities the urban gradient remains clearly visible: practically every amenity they can measure seems to improve with population density. The authors interpret this as evidence in favour of a friction model in which people's mobility is somehow resticted, which allows the spatial disequilibrium to persist. Support for this view from our setting in Tanzania comes from Ingelaere et al. (2018) who show that there is a widespread desire to move out of the rural areas and into larger urban agglomerations, especially by younger people. Despite their acute awareness of the spatial differences in living standards, for the average young person living in a remote villlage, moving is considered a daunting, sometimes impossible, endeavour.

We use household survey and census data from Tanzania to confirm rising living standards across the urban spectrum, from rural areas over towns to cities. That urban gradient is visible both in terms of assets and housing wealth as well as amenities. Overlaying the wealth distributions, we find that living standards of the 90th percentile in rural areas still lie below those of the 10th percentile in urban areas. This is problematic for the basic Todaro (1969) model, which assumes that the rural wage needs to equal the weighted average of the high and low urban wage, with the weights being the likelihood of getting each. We consider an extension of the basic model that introduces migration costs, which include the transport costs, set-up costs and risk associated with the move and so forth. In our setting these costs increase with distance (Ingelaere et al. 2018), which is why we will sometimes refer to them as transportation costs. Transportation costs bring the Todaro model back in line with the empirical observation in our setting that that the rural wage is lower than both the lower and higher urban wage. The second extension to the model is to introduce multiple destinations (town or city), each characterised by different formal and informal destination wages (Kanbur et al., 2017).

Guided by this model we use a novel data set on migrants for whom we have pre-migration and post-migration survey data. At baseline in the early 1990's the respondents all lived in Kagera, a large, remote and primarily rural region in the north-western part of Tanzania, but by 2010 about half of those who were still alive had moved out to other villages, towns or cities. We use the pre-migration survey data to create a dyadic dataset of all possible migrant-destination pairs, out of which the migrant will have chosen one and not chosen all others. We then use census data to construct measures of the basic Todaro building blocks (expected wages and transport costs), allowing us to test the relative importance of each.

We find that distance plays an important role, accounting for three quarters of the explained variation for those moving to urban areas and 98% for those moving to rural areas.

We then discuss how small towns are becoming an increasingly important part of the urban landscape in Africa. Because their rise is geographically quite well spread out, they are a powerful force reducing the distance between rural and urban areas. For the average rural migrant it is likely that the distance to the nearest small town is of an order of magnitude smaller than the distance to a large city. And with every new small towns that comes into existence that distance reduces further, on average. This reduction in distance reduces mobility frictions and opens up lucrative migration opportunities for a larger share of the population.

2 Data and the urban gradient

This section introduces our two data sources: Kagera Health and Development Survey (KHDS) and the 2002 Tanzania Population and Housing Census. Within each we demonstrate rising living standards from villages across towns to cities, which we refer to as the urban gradient. In KHDS the gradient is demonstrated for changes in migrant welfare in a panel data set, while in the census it is shown to hold cross-sectionally for all residents of these areas.

2.1 KHDS

The Kagera Health and Development Survey (KHDS) is a study into the long-run wealth dynamics of households and individuals within North West Tanzania. This study entails the resurvey of a panel of households, originally interviewed for 4 rounds from 1991 to 1994. Resurveys were then organised in 2004 and 2010. A multi-topic household questionnaire is administered to all split-off households originating from the baseline households, including those that have moved out of the baseline location.

This constitutes one of the longest-running African panel data set of this nature and offers an unprecedented set of research opportunities for examining long-run (nearly 20 years) trends in and mechanisms of poverty persistence and economic growth in rural households. As the children of the original respondents have now formed their own households, intergenerational issues can be addressed by the survey data. Interviewing people who moved out of their baseline location is important for understanding how migration and economic development interlink. The data is of particularly high quality and the 2010 round of the survey was conducted using electronic survey questionnaires administered on handheld computers, with automated skips and validation checks run during the interview when errors could be corrected at source. The resulting improvements in data quality have been formally assessed by Caeyers et. al. (2012).

KHDS has maintained a highly successful tracking rate. Table 1 shows that in 2010 88%

Table 1: KHDS response rates

	2004	**2010**
Interviewed	4430 (70%)	4339 (68%)
Deceased	961 (15%)	1275 (20%)
Untraced	962 (15%)	739 (12%)
TOTAL	**6353 (100%)**	**6353 (100%)**

of the original 6353 respondents had either been located and interviewed, or, if deceased, sufficient information regarding the circumstances of their death collected.

In 2010, households were found in three cities: Dar es Salaam, Mwanza and Kampala. This is defining cities as locations (districts) with more than 500,000 inhabitants. The 2012 census puts the population of Dar es Salaam at 4.36m and Mwanza at 0.7m.[1] There are a further 21 respondents who moved to areas that, while administratively recognized within Tanzania as cities, have a population below 500,000 (Arusha, Tanga and Mbeya). Results do not change if we change the definition from a population-based one to an administrative one. All KHDS locations were matched with their census ward-level classification, which distinguish between urban, mixed or rural areas. All urban and mixed areas are classified as towns (or cities if in Mwanza, Dar or Kampala) and all rural areas classified as rural. Fortunately the KHDS CAPI application had a series of conditional drop-down menus where the interviewer chose region, district, ward and village in which the household was located. These were pre-populated with the exact census locations and codes, so that the matching exercise is perfect. The census classification is based on 2002 data and the average migrant respondent in our survey moved in 2003.

The consumption data originate from extensive food and non-food consumption modules in the survey, carefully designed to maintain comparability across survey rounds and controlling for seasonality. The consumption aggregate includes home produced and purchased

[1] For Mwanza this is the sum of Nyamagana Municipal Council (363,452) and Ilemela Municipal Council (343,001). More detailed analysis using 2002 census data [[Wenban-Smith, 20??]] showed that while the municipal districts of Mwanza counted a population of 596,885, only 65% of these lived in strictly urban wards (others lived in rural or mixed wards). The current census does not yet disclose the new categorisations, but applying the same rural-urban ration of 65% to the current census figure gives us an urban population of 456,631. This estimate lies under 500k, but we decide to treat Mwanza as a city based on the district-level figures.

food and non-food expenditure. The non-food component includes a range of non-food purchases, as well as utilities, expenditure on clothing/personal items, transfers out, and health expenditures. Funeral expenses and health expenses prior to the death of an ill person were excluded. Conservatively, rent is also excluded from the aggregate to avoid large differences in prices for similar quality housing being the driver of any measured urban-rural disparities. The aggregates are temporally and spatially deflated using data from the price questionnaires included in each survey round. As household size may differ between urban and rural households, consumption is expressed in per adult equivalent units rather than per capita. The poverty line is set at 326,474.2 Tanzanian shillings (TSh)[2], calibrated to yield for our sample of respondents who remained in Kagera the same poverty rate as the 2007 National Household Budget Survey estimate for rural areas (37.6 percent).

Unless otherwise indicated the analysis below is conducted at the individual level.

A basic stylized fact that came out of the decomposition analysis of Christiaensen et al. (2019), and illustrated again in Table 2, is that moves to cities are more lucrative for those who make them, but that many more migrants find their way to the secondary towns. Figure 1 shows that where there was no stochastic dominance between future town migrants and future city migrants during the early nineties at baseline, there was clear stochastic dominance by 2010. For migrants to rural areas the stochastic dominance was already present at baseline and gets exacerbated by the endline (except for consumption per capita values to the far right of the distribution, where one would unlikely want to place a poverty line). There is a clear urban gradient to poverty, just as in Ferre et al. (2012) and Lanjouw and Marra (2018).

2.2 Census

The KHDS survey informs us on the plight of the average Kagera migrant at the different destinations. This section will look at the general population characteristics across the whole of Tanzania. We make use of the 2002 Tanzania Population and Housing Census, conducted on the night of 24 August 2002. The data, made available by Minnesota Population Center

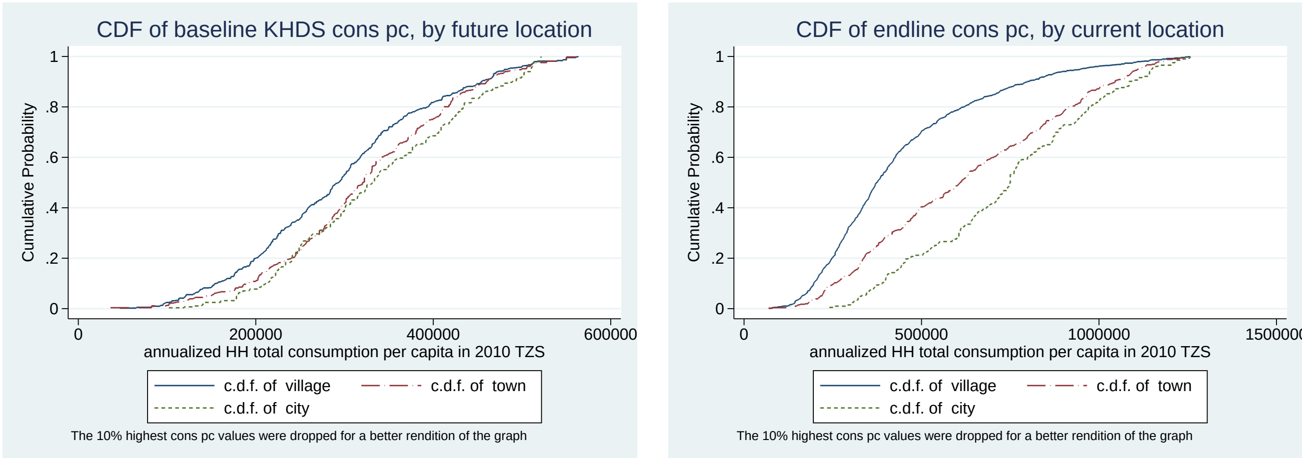
[2] At the time of the survey one US dollar was worth around TSh 1,450

Table 2: Decomposing growth and poverty reduction by 2010 location (collapsed version)

			Growth (consumption per capita)		
2010 Location	*N*	1991-94 average	2010 average	Change in average	Share in total growth
Rural	1,086	347,433	573,281	225,848	0.29
Town	702	390,934	906,228	515,293	0.43
City	285	400,836	1,229,495	828,659	0.28
TOTAL	2,073	369,617	776,247	406,630	1.00

			Poverty headcount		
2010 Location	*N*	1991-94	2010	Change in headcount	Share in total net poverty reduction
Rural	1,086	0.56	0.35	-0.21	0.40
Town	702	0.45	0.14	-0.31	0.38
City	285	0.45	0.02	-0.42	0.21
TOTAL	2,073	0.50	0.23	-0.27	1.00

			Poverty gap		
2010 Location	*N*	1991-94	2010	Change in gap	Share in total gap change
Rural	1,086	0.17	0.10	-0.07	0.48
Town	702	0.11	0.03	-0.08	0.34
City	285	0.11	0.00	-0.10	0.19
TOTAL	2,073	0.14	0.06	-0.08	1.00



Baseline CDF

Endline CDF

Figure 1: Comparison of baseline and endline consumption per capita, by 2010 location (KHDS)

(2014), contains long form census data on over 3.7 million individuals in the country, which can be disaggregated by district, and within each district by rural and urban areas, giving a total of 254 geographical areas to potentially consider.

The long form sample contains basic census information, such as the age and sex of all members, from which we can derive household size and a dependency ratio. Information on housing characteristics includes the number of bedrooms in the dwelling and the materials out of which the roof, walls and floors are made. Further details on utilities allow us to calculate who has electricity, piped water and a flush toilet. We further know about asset ownership. For each individual there is information on their employment status and the industry or sector they work in.

Many of the variables collected reflect the wealth of the household. It will be useful below to construct, from these, a single wealth variable. Lacking weights, such as prices, to meaningfully add up the various wealth components available in our data, we reduce the dimensionality of our wealth data by extracting the first principal component of a number of housing, utility and asset outcomes of sampled households.

We then use variation in wealth index across households to construct a measure of inequality at each locations. We do this by dividing the standard deviation of the wealth index at the location by the square root of the eigenvalue corresponding to the first principal component.

This follows as suggestion by McKenzie (2004) who shows that such an inequality indicator has a number of desirable properties such as anonymity, scale independence, population independence and the Pigou-Dalton property.

We use the following variables for the principal component analysis: number of bedrooms per person, whether the dwelling has an iron sheet roof (or better), walls from baked bricks (or better), a tile or cement floor, electric lighting, piped water, a flush toilet and whether it owns a radio, owns a phone and owns an iron. This combines housing and other assets with amenities. In some of the analysis it will be useful to distiguish between these two types of wealth, so we also create a separate asset index based on variables that relate purely to housing and other asset wealth (number of bedrooms per person, type of roof, wall, or floor and ownership of radio, iron and phone), as well as an amenities index based purely on the subset of variables relating to amentities (availability of electric lighting, piped water and flush toilet).

The basic stylized fact arising from Figure 2 and Table 3 is one of a clear gradient with living standards improving as one moves from villages over towns to cities, in line with what Gollin et al. (2017) document for much of the developing world.

Housing, utilities and assets outcomes improve along the urban gradient, which is reflected in a constructed wealth index which is much higher in towns than in rural areas and higher still in cities compared to towns. The inequality index is much lower in rural areas and higher in urban areas. We see that, with respect to the constructed wealth index, the 10th percentile in cities already outperforms the 90th percentile in rural areas. Of note is also that urban households are smaller, younger and their members have more years of formal education. The census asks whether the household experienced any death among its members in the 12 months preceding the interview, followed by a question on the sex and age of the deceased. Somewhat fewer urban households were bereaved and in cities the age of the deceased is higher, although the size effects are not large. With respect to employment, we note that very few rural households have a non-seasonally employed member, but respectively 24% and 38% of town and city households do. Finally, while only 9% of households have a member working outside of the agricultural sector in rural areas, 54% and 74% do so in towns and cities.

Table 3: Census location means

	Rural	**Town**	**City**
At least corrugated iron sheet roof	0.33	0.84	0.99
At least baked brick walls	0.18	0.52	0.88
At least tile or cement floor	0.11	0.62	0.88
Electric lighting	0.01	0.29	0.45
Piped water	0.21	0.68	0.77
Flush Toilet	0.00	0.11	0.16
No. bedrooms	2.29	2.20	2.08
No. bedrooms per person	0.71	0.71	0.72
GoodElec	0.01	0.27	0.42
Owns Radio	0.45	0.67	0.75
Owns Phone	0.01	0.08	0.20
Owns Iron	0.03	0.07	0.09
No. members age 19 or younger	2.68	2.14	1.83
No. members age 20-60	1.82	1.86	2.11
No. members age 61 or older	0.26	0.15	0.10
Household size	4.76	4.15	4.04
Dep. ratio (as share of 20-60 year olds)	1.71	1.27	0.94
Maximum years of formal education in HH	6.70	8.01	8.64
HH experienced death past 12 months	0.06	0.05	0.05
Age died (if deceased past 12 months)	23.20	27.81	27.13
At least one member non-seasonal employee	0.05	0.24	0.38
At least one member works in non-ag sector	0.09	0.54	0.74
Wealth index	-0.46	0.79	1.48
Wealth index at 10th percentile	-0.99	-0.65	0.33
Wealth index at 20th percentile	-0.99	-0.23	0.75
Wealth index at 80th percentile	-0.09	1.80	2.34
Wealth index at 90th percentile	0.29	2.65	2.73
Inequality index	0.34	0.63	0.55
Amenities index	-0.37	0.73	1.18
Asset index	-0.44	0.69	1.38

Notes: Averages are constructed using the census long form survey weights. Only Dar es Salaam and Mwanza are considered cities. The constructed wealth index is the first principal component using the following variables: number of bedrooms per person, whether the dwelling has an iron sheet roof (or better), walls from baked bricks (or better), a tile or cement floor, electric lighting, piped water, a flush toilet and whether it owns a radio, owns a phone and owns an iron. The constructed inequality index is variance of constructed wealth index in subgroup relative to variance in total sample (McKenzie, 2004).

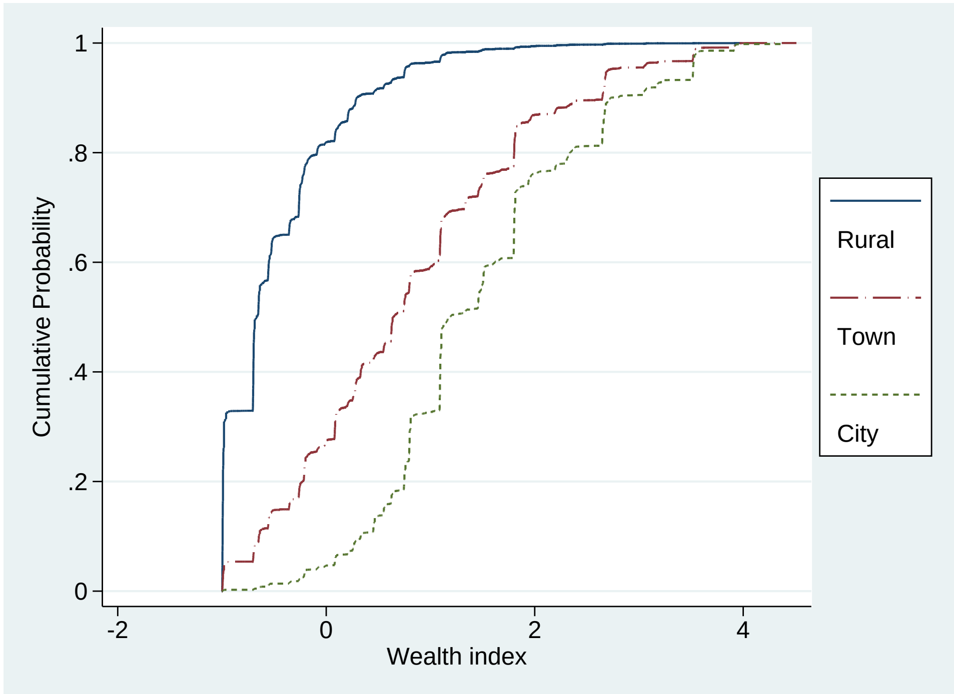


Figure 2: CDF of census-based wealth index, by location (population-weighted)

2.3 Linking the KHDS and Census Data

The 2002 population and housing census was conducted roughly half way between our baseline and endline surveys and provides sufficient granularity to describe the various destinations of the KHDS respondents. To do that we match the various KHDS destinations with their location characteristics from the census. Above we noted that our census identifies 254 destinations. Respondents in our sample moved to 78 out of these 254 destinations. These represent the urban and/or rural locations in 57 districts. We can match each KHDS migrant to the location characteristics of the place they are currently residing. We start analysing these linked data in Table 4, where we average the location characteristics at destination across the KHDS internal migrants, broken down into those who moved to rural areas, towns or cities. The table shows the location characteristics, as measured by the 2002 census, experienced by the average KHDS migrant who has migrated to either of these three locations.[3] Not surprisingly we see a repetition of the same patterns as above, indicating that the migrants from our sample do not seek out destinations that deviate much from the

[3]That means they are averages of location characteristics across individuals, which is the same as saying they are location averages weighted by the number of KHDS migrants at each location.

average.

For some of the analysis below we will link urban migrants to all 47 urban locations and all rural migrants to all 31 rural locations.

3 The extended Todaro model

The previous analysis has highlighted at least two stylized facts, which are not in line with the basic Todaro (1969) model. First, urban welfare levels clearly dominate rural welfare levels. This is true when we look at data on those who migrate to these locations in the KHDS, or on all those residing there in the census data. In the census, for example, Table 3 shows the constructed wealth index in the rural areas going from -0.99 at the 10th percentile to 0.29 at the 90th percentile, while in cities these same percentiles span 0.33 to 2.73: even the lowest city welfare level, measured this way, outperforms that of the highest rural ones. Similarly, KHDS shows that moves to towns or cities clearly outperform not moving or moves to rural areas.

These facts are problematic for the original Todaro model, as the model requires rural wages to equate the expected city wages in equilibrium. Kanbur et al. (2017) extend the model by introducing a cost to moving for each migrant (financial, social, psychological,...). The equilibrium condition now requires that rural wage plus costs need to equal the expected urban wage, so that there is a range of costs that can make the Todaro model fit the stylized facts.

Second, both KHDS and the census show that the economy is not dualistic, but displays a clear gradient from villages, over towns to cities. Thus, the second extension the authors make to the Todaro model is the introduction of multiple destinations.

The model highlights the role of a number of key variables when it comes to destination choice: the cost of moving and the destination wages. The next section introduces these variables into a regression framework to assess their relative importance and their interaction with poverty, education and age.

Table 4: Census means averaged across KHDS migrants, by destination

	Rural	**Town**	**City**
UrbanPM	1.00	2.00	3.00
At least corrugated iron sheet roof	0.54	0.93	0.98
At least baked brick walls	0.14	0.63	0.79
At least tile or cement floor	0.12	0.68	0.84
Electric lighting	0.02	0.28	0.39
Piped water	0.10	0.42	0.78
Flush Toilet	0.00	0.08	0.16
No. bedrooms	2.50	1.92	2.02
No. bedrooms per person	0.75	0.66	0.69
Owns Radio	0.46	0.68	0.76
Owns Phone	0.01	0.07	0.19
Owns Iron	0.03	0.06	0.08
No. members age 19 or younger	2.63	2.03	1.91
No. members age 20-60	1.67	1.78	2.07
No. members age 61 or older	0.26	0.10	0.10
Household size	4.56	3.91	4.08
Dep. ratio (as share of 20-60 year olds)	1.77	1.20	1.00
Maximum years of formal education in HH	6.76	8.06	8.55
HH experienced death past 12 months	0.07	0.04	0.05
Age died (if deceased past 12 months)	24.56	24.37	27.18
At least one member non-seasonal employee	0.06	0.27	0.37
At least one member works in non-ag sector	0.12	0.59	0.72
Constructed wealth index	-0.42	0.79	1.37
Wealth index at 10th percentile	-0.99	-0.39	0.22
Wealth index at 20th percentile	-0.95	-0.00	0.54
Wealth index at 80th percentile	-0.04	1.46	2.21
Wealth index at 90th percentile	0.34	2.03	2.76
Constructed inequality index	0.32	0.50	0.56
No. KHDS migrants at this location	1,036.00	628.00	332.00

Notes: First the averages are calculated for each district-urban/rural combination. These are then linked to KHDS migrants at each location and averaged over all rural, town and city location, i.e. the last averaged is weighted by the number of KHDS migrants at each location (see last row with N). The constructed wealth index is the first principal component using the following variables: number of bedrooms per person, whether the dwelling has an iron sheet roof (or better), walls from baked bricks (or better), a tile or cement floor, electric lighting, piped water, a flush toilet and whether it owns a radio, owns a phone and owns an iron. The constructed inequality index is variance of constructed wealth index in subgroup relative to variance in total sample (McKenzie, 2004).

We use distance to destination as a proxy for the cost of moving. That choice is grounded in the work of Ingelaere et al. (2018), who conduct detailed life history interviews with 75 respondents sampled from the Kagera Health and Development Survey (KHDS), the same survey underlying the analysis in this paper. These authors show how respondents themselves, when narrating their life histories, talked about distance as an impediment to moving: it raises the cost of moving, it complicates returning home to visit or when things go wrong at destination, it makes it difficult to maintain ties, can erode informal property rights and typically comes with higher cultural barriers to moving.

4 Econometric analysis of destination choice

4.1 Set-up

If we are to understand destination choice among migrants then it is as important to know where the migrant migrated to as it is to know which potential destinations the migrant did not migrate to. We noted before that our internal migrants have moved to 57 different districts, within which we further distinguish moves to rural or urban areas to arrive at a total of 78 locations. Our analysis makes the assumption that these 78 locations are the potential destinations for our sample of migrants.

Each of the migrants in our sample has chosen to move to one potential destination; and has therefore also chosen *not* to move to the 77 other potential destinations. In order to understand that choice better, we create a dyadic data set that contains 78 observations for each migrant i; one observation for each potential destination d. Our dependent variable Y_{id} is a dummy equal to one if i was found in location d during the last survey round and zero otherwise. Our analysis will consist of studying the correlates of Y_{id}. This kind of dyadic analysis has been used before to understand destination choice by Fafchamps and Shilpi (2013). We follow these authors in analysing only those who have actually migrated in order to not confound the destination choice with the migration choice. We also analyse separately those who have moved to rural areas and those who have moved to urban areas.

Destination choice Y_{id} will depend on the observed and unobserved characteristics of the individual (including those related to household and community circumstances), the destination (such the standard of living the migrant would expect to achieve at destination) and the relation between the individual and the location (such as distance to destination or the interaction between the individual's wealth level and the destination's wealth level).

Our data set-up has 78 observations per individual, which allows us to address observed and unobserved individual characteristics of the individual by including an individual fixed effect α_i in the regression. Another econometric concern is whether the structure of the error terms is influenced by the baseline survey's two-stage sampling design. We therefore report standard errors that account for clustering within each of the 51 KHDS villages of origin, which were the primary sampling units in the baseline survey (Abadie et al., 2017).

The key independent variables of interest include the characteristics of the destination district in vector $\mathbf{D}_d$ and relational variables in vector $\mathbf{R}_{id}$ that are specific to the $i-d$ pair, such as distance of d to i's baseline village or individual characteristics such as education interacted with destination characteristics. We do not include any individual, household or community level effects as these are controlled for by the inclusion of the individual fixed effect α_i.

We then estimate the following equation:

$$Y_{id} = \mathbf{D}_d\beta_1 + \mathbf{R}_{id}\beta_2 + \alpha_i + \epsilon_{id}, \tag{1}$$

where ϵ_{id} is an error term.

In our most basic regression set-up we populate $\mathbf{D}_d$ with W_d, the average wage at destination and $\mathbf{R}_{id}$ with the natural logarithm of the km distance of the destination district to the baseline community.[4]

[4] W_d combines a number of basic building blocks in the original Todaro model: formal sector wage, informal sector wage and sectoral employment rates. Distance is a proxy for moving costs, as explained in Section 3

4.2 Results

In the first column of Table 5 we estimate Equation 1 on a dyadic data set that links all migrants to all destinations. Both wealth and distance are significantly correlated to destination choice, with opposite signs: the further away the potential destination the less likely it will be chosen and the wealthier it is the more likely it will be chosen. The (absolute) magnitude of the distance coefficient is 4 times that of the wealth coefficient. Multiplying those coefficients by the standard deviations of the corresponding variables in the dyadic data set (0.97 for distance and 0.71 for wealth), we see that wealth would need to go up by 5.7 standard deviations to offset the negative effect of a one standard deviation increase in distance.

In the second, third and fourth columns of Table 5 we interact distance and wealth with individual characteristics: baseline poverty status (1=poor), age and years of formal education. Coming from a poor baseline household increases the negative effect of distance and decreases the pulling effect of high wealth at destination. Similarly, education attenuates the friction related to distance and enlarges the pull of high wealth areas. Interactions with age show that older people are less affected by distance, but there is no significant interaction with wealth.

Our wealth index includes both housing and other asset wealth, as well as amenities. In the final column of Table 5 we investigate whether either of these components dominates destination choice. To do this we revert back to the sample of column 1, but now enter separate indices for each of these components of wealth as well as their interaction. The first is the asset index, which uses number of bedrooms per person, whether the dwelling has an iron sheet roof (or better), walls from baked bricks (or better), a tile or cement floor, whether the housheold owns a radio, owns a phone and owns an iron. The second is the amenities index, based on whether the household has electric lighting, piped water and flush toilet.[5] We see that only the interaction of the two indices is statistically significant, suggesting that neither the assets nor the amenities component dominate the effects of the wealth index, but both are complementary to each other.

[5]The wealth index used in the other columns is constructed using the union of the variables used in the asset and amenities index.

In the fifth column of Table 5 we explore whether distance and wealth have different effects depending on whether the potential destination is urban or rural. To look at this, we include a dummy variable indicating the urban status of the destination as a regressor, as well as its interactions with distance and wealth. We see no differences for wealth, suggesting that the pull of wealth differences do not differ between urban and rural destinations. We do see significant interaction effects with distance: the rate at which distance deters migration is twice as high for rural destinations than for urban destinations.

We explore these differences between urban and rural migrants further by altering how we form the dyads. In Table 6 we link all urban migrants to all 47 urban locations. For urban migrants selecting urban locations distance and wealth are both significantly associated with destination choice, with coefficients roughly of equal absolute magnitude. As a per standard deviation change the absolute magnitude for distance (sd=0.91 in this dataset pairing urban migrants with urban destinations) is 1.6 times greater than that for wealth (sd=0.50). In Table 7 we link all rural migrants to all 31 rural locations. Again, both distance and wealth matter, but expressed in standard deviation change (sd=1.03 for distance and a much lower sd=0.20 for wealth in the rural-rural dyadic dataset) distance outweighs wealth by a factor of 7.5.

In further iterations we explore the interactions between distance and wealth with individual characteristics, for urban migrants linked to all potential urban destinations (Table 6) and rural migrants linked to all potential rural destinations (Table 7). For urban migrants, the interactions show that the pulling power of urban destination wealth is reduced for poorer households, while it increases for households with more education. For rural migrants there are no significant interaction effects with wealth coming from poverty status or years of schooling, but there is a small negative interaction effect between age and wealth. There are no interaction effects between distance and poverty or between distance and age in the urban or rural destinations samples. The effect of schooling, on the other hand, is similar in direction and statistiscal signficance across the urban and rural destination tables. Each year of additional formal eduction reduces the negative effect of distance on destination choice, but it does so at a steeper gradient for urban migrants compared to rural migrants.

For all three dyadic samples these basic regressions highlight how distance dominates wealth as a correlate of distanation choice. A Shapley decomposition for the regressions in columns 1 of Table 5 shows that distance accounts for 98% of explained variation of destination choice in the full sample. A similar exercise for column 1 of Table 6 shows that distance accounts for 75% of the explained variation once we restrict the analysis to dyads formed by urban migrants choosing between urban locations.

We should bear in mind that the R-squares are quite low in all regressions (between 4 and 17 percent). This is for a large part due to the fact that we are considering a large number of possible destinations for each person (47 urban and 31 rural destinations), but is also a reminder that distance does not tell the whole story. Despite the low R-square, it is obvious from the F-test for joint significance of all regressors reported in the table that, taken together, wealth and distance are important determinants of destination choice.

5 Small towns in Tanzania

5.1 The rise and geographical spread of small towns

Urbanisation in Tanzania has been characterised by the rise of the small town. At the time of the 1967 census 95% of the Tanzanian population lived in rural areas and the urban areas were restricted to Dar es Salaam, with a population of only 270,000 and 20 regional capitals out of which only 14 had a population larger than 10,000. 45 years later, by the time of the 2012 census, 30% of the population lived in urban areas. These were split roughly equally across Dar es Salaam, the regional capitals and other urban areas. Dar es Salaam had a population of 4.4m, the 20 original regional capitals had an average size of over 200,000 and there were 117 other urban centres with a population larger than 10,000. Our analysis suggests it is primarily the lower distance to these towns that explains their succes as preferred destination for rural migrants.

Figure 3 plots population census data over 6 censuses conducted in Tanzania, from 1957-2012. These data were put together by Wenban-Smith (2015) from the various census reports and provide a unique perspective on 55 years of demographic development in Tanzania. The

Table 5: Destination choice of migrants - dyadic regressions

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Distance to destination (ln km)	-0.025***	-0.023***	-0.039***	-0.023***	-0.035***	-0.027***
	(-21.176)	(-18.077)	(-31.178)	(-14.512)	(-13.328)	(-17.531)
(-”-) * (poor HH)		-0.003*				
		(-1.825)				
(-”-) * (yrs schooling)			0.002***			
			(12.043)			
(-”-) * (age in years)				-0.000		
				(-1.589)		
(-”-) * (urban destination)					0.019***	
					(5.527)	
Wealth index	0.006***	0.009***	-0.006***	0.009***	0.022***	
	(6.062)	(8.244)	(-5.880)	(6.031)	(4.390)	
(-”-) * (poor HH)		-0.006***				
		(-4.642)				
(-”-) * (yrs schooling)			0.002***			
			(12.496)			
(-”-) * (age in years)				-0.000***		
				(-2.821)		
(-”-) * (urban destination)					-0.003	
					(-0.535)	
Urban destination					-0.141***	
					(-6.455)	
Asset index						-0.003
						(-0.856)
Amenities index						-0.002
						(-0.486)
(Asset index)*(Amenities index)						0.020***
						(7.231)
R-square	.0443	.0449	.0497	.0444	.0561	.049
F	827	427	568	414	433	590
p-value F	0.000	0.000	0.000	0.000	0.000	0.000
N	156,936	155,688	156,936	156,936	156,936	156,936

Notes: LPM estimates of Equation 1 with standard errors clustered by the 51 origin enumeration areas. Regression coefficients with t-statistics in parentheses. The dyads are formed by linking all 2,012 KHDS migrants to all possible 78 destinations. Destination wealth is the average household wealth index at destination calculated from the census. The wealth index is the first principal component using the following variables: number of bedrooms per person, whether the dwelling has an iron sheet roof (or better), walls from baked bricks (or better), a tile or cement floor, electric lighting, piped water, a flush toilet and whether it owns a radio, owns a phone and owns an iron. The amenities index is constructed in a similar fashion using a subset of these variables (electric lighting, piped water and flush toilet) and the asset index is constructed using all the other variables. Distance is the natural logarithm of distance in kilometers between the baseline location and the potential destination, as the crow flies.

Table 6: Destination choice of urban migrants - interactions

	(1)	**(2)**	**(3)**	**(4)**
Distance to destination (ln km)	-0.033***	-0.035***	-0.063***	-0.031***
	(-12.249)	(-10.987)	(-15.508)	(-5.657)
(-”-) * (poor HH)		0.003		
		(0.786)		
(-”-) * (yrs schooling)			0.004***	
			(8.516)	
(-”-) * (age in years)				-0.000
				(-0.327)
Wealth index	0.038***	0.042***	0.024***	0.040***
	(11.866)	(12.680)	(3.124)	(10.626)
(-”-) * (poor HH)		-0.008**		
		(-2.274)		
(-”-) * (yrs schooling)			0.002***	
			(2.787)	
(-”-) * (age in years)				-0.000
				(-0.383)
R-square	.0485	.049	.0547	.0485
F	240	130	294	133
p-value F	0.000	0.000	0.000	0.000
N	45,449	45,120	45,449	45,449

Notes: LPM estimates of Equation 1 with standard errors clustered by the 51 origin enumeration areas. The dyads in the first and fourth column are all migrants linked to all possible destinations. Regression coefficients with t-statistics in parentheses. The dyads in the second column are all urban migrants linked to all potential urban destinations. The dyads in the third column are all rural migrants linked to all potential rural destinations. Destination wealth is the average household wealth index at destination calculated from the census. The wealth index is the first principal component using the following variables: number of bedrooms per person, whether the dwelling has an iron sheet roof (or better), walls from baked bricks (or better), a tile or cement floor, electric lighting, piped water, a flush toilet and whether it owns a radio, owns a phone and owns an iron. The amenities index is constructed in a similar fashion using a subset of these variables (electric lighting, piped water and flush toilet) and the asset index is constructed using all the other variables. Distance is the natural logarithm of distance in kilometers between the baseline location and the potential destination. Poverty information comes from the baseline household in which i was residing in 1991-94. Education is measured as years of formal education at baseline.

Table 7: Destination choice of rural migrants - interactions

	(1)	(2)	(3)	(4)
Distance to destination (ln km)	-0.071***	-0.066***	-0.083***	-0.071***
	(-29.180)	(-26.434)	(-22.623)	(-23.494)
(-"-) * (poor HH)		-0.007**		
		(-2.181)		
(-"-) * (yrs schooling)			0.002***	
			(5.180)	
(-"-) * (age in years)				0.000
				(0.146)
Wealth index	0.049***	0.065***	0.017*	0.063***
	(6.186)	(6.401)	(1.961)	(6.282)
(-"-) * (poor HH)		-0.026**		
		(-2.214)		
(-"-) * (yrs schooling)			0.006***	
			(4.612)	
(-"-) * (age in years)				-0.000**
				(-2.203)
R-square	.172	.172	.174	.172
F	740	380	390	376
p-value F	0.000	0.000	0.000	0.000
N	32,395	32,116	32,395	32,395

Notes: LPM estimates of Equation 1 with standard errors clustered by the 51 origin enumeration areas. Regression coefficients with t-statistics in parentheses. The dyads are all rural migrants linked to all potential rural destinations. Destination wealth is the average household wealth index at destination calculated from the census. The wealth index is the first principal component using the following variables: number of bedrooms per person, whether the dwelling has an iron sheet roof (or better), walls from baked bricks (or better), a tile or cement floor, electric lighting, piped water, a flush toilet and whether it owns a radio, owns a phone and owns an iron. The amenities index is constructed in a similar fashion using a subset of these variables (electric lighting, piped water and flush toilet) and the asset index is constructed using all the other variables. Distance is the natural logarithm of distance in kilometers between the baseline location and the potential destination. Poverty information comes from the baseline household in which i was residing in 1991-94. Education is measured as years of formal education at baseline.

first panel breaks the total population down into those living in rural areas, Dar es Salaam, regional capitals and other urban areas. The graph clearly shows how Tanzania's urban population is making up an increasingly larger share of the nation's total population, from a tiny fraction in 1967 to nearly 30% by the time of the 2012 census.

Let us now look at the nature of the urbanisation process, by plotting urban composition from 1957-2012 in the lower panel of Figure 3. At the last census in 2012, about one third of the urban population lived in Tanzania's primary city, Dar es Salaam. Another third lived in 20 regional capitals[6], while the final third lived in 117 smaller secondary towns. The latter contained at least 10,000 inhabitants and are not regional capitals. Dar has a population of 4.4 million, the average regional capital of 200,000 and the average smaller secondary town of 20,000.

The graph provides an interesting historical perspective. First, we can see that Dar es Salaam has maintained a stable one third of the urban population over the past half century. At the same time Dar has grown in absolute numbers from 2.3m in 2002 to 4.4m by 2012, currently accommodating 10% of Tanzania's population. So while its primacy is beyond doubt it is incorrect to think that it is taking up a larger share of the urban population. A second important historical trend is the rise to prominence of the smaller secondary towns, not categorised as regional capitals. Whereas by 1978 there were only 15 such towns, Wenban-Smith (2015) counts 39 of them by 1988, 80 by 2002 and 117 by 2012.

The rise of the small town is not just a Tanzanian phenomenon, but is happening across the continent. Moriconi-Ebrard et al. (2016) use demographic and satellite data for 17 West African countries to show how the number of agglomerations in this region went up from 152 in 1950 to a little under 2,000 in 2010.

And within Tanzania the rise of the small town is not specific to any particular region or district; new small towns are arising all over the country. For some preliminary evidence on this we turn to a very recent exercise conducted by the OECD's Africapolis, which extends the methodology of Moriconi-Ebrard et al. (2016) to the whole African continent and includes data on Tanzania's urban agglomeration. A disadvantage of this data set is

[6] defined historically, not taking into account recent splits of regions

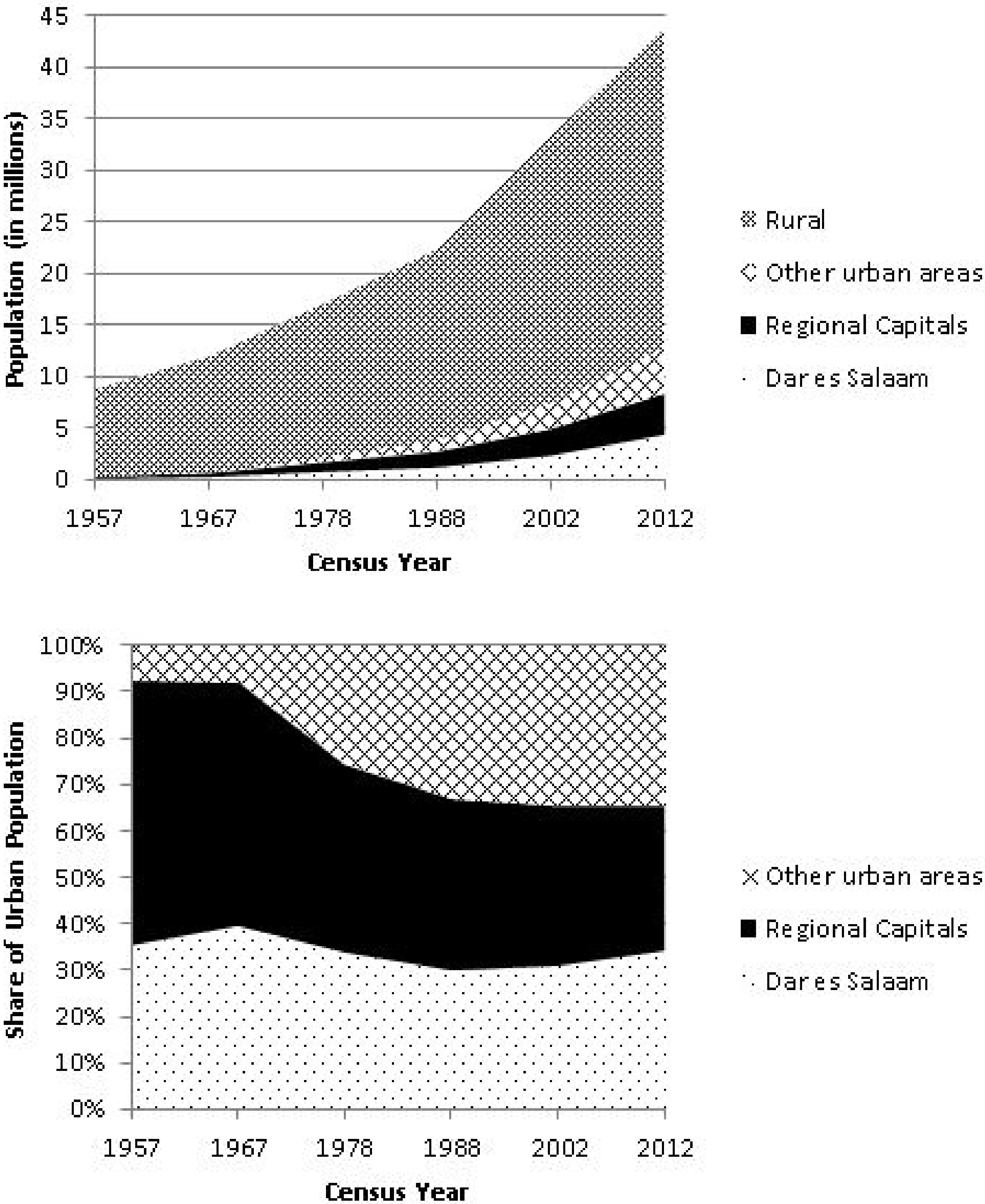


Figure 3: Historical trend of urban composition (source: adapted from Wenban-Smith, 2015)

that it cannot show historical trends. An advantage, however, is that it is georeferenced and includes an estimate of the total population at each urban agglomeration. We can use those two last features to map, as we do in the bottom half of Figure 4, Tanzania's small towns (population 10-100k), big towns (population 100-500k) and cities (population >500k). That exercise makes it very clear that these agglomerations are not concentrated in any particular area.[7]

5.2 Small towns and shrinking rural-urban distance

This diffuse geographical spread of small towns is important for our argument, because with every new small town (a subset of) rural dwellers will see the distance between their home village and the nearest urban agglomeration shrink. This, in turn, reduces the frictions to rural-urban migration. It also makes moves to small towns more attractive and more likely that small towns are chosen as urban migration destinations.

We can calculate the extent to which this happens by combining the econometric estimates of destination choice from the previous section with data on distance of KHDS villages (which are KHDS's rural Enumeration Areas) to urban agglomerations identified in Africapolis. Before we embark on that exercise it is useful to bear two caveats in mind. First, Kagera, like any region has its own geographical specificities, as can be seen from the map in Figure 4. For example, Kagera is a relatively remote region with, within its borders, only one large town (Bukoba) and no cities. The closest city is Mwanza on the southern shores of Lake Victoria, while Tanzania's prime city, Dar es Salaam, is located at the other end of the country. In short Kagera is a relatively remote region and that should be kept in mind when interpreting this exercise. Second, the urban agglomerations we consider here do not overlap with those used in the dyadic analysis. Unfortunately neither Africapolis, nor

[7] Africapolis counts 249 urban agglomerations in Tanzania for 2015, while Wenban-Smith counts 138 in 2012. No doubt some of this difference is due to the difference in timing, but the probable prime reason for the discrepancies is that Wenban-Smith's data depend, for the identification of urban areas, on official designation in the census, while the Africapolis data combines census and satellite data. The Africapolis data show also Mbeya and Arusha as having populations exceeding 500,000 in mainland Tanzania, but we do not consider them as cities here to remain consistent with the previous analysis. As noted earlier, very few of our respondents moved to these places, so these choices have no bearing on our findings. We accessed the Africapolis data at http://www.africapolis.org on 3 January 2019.

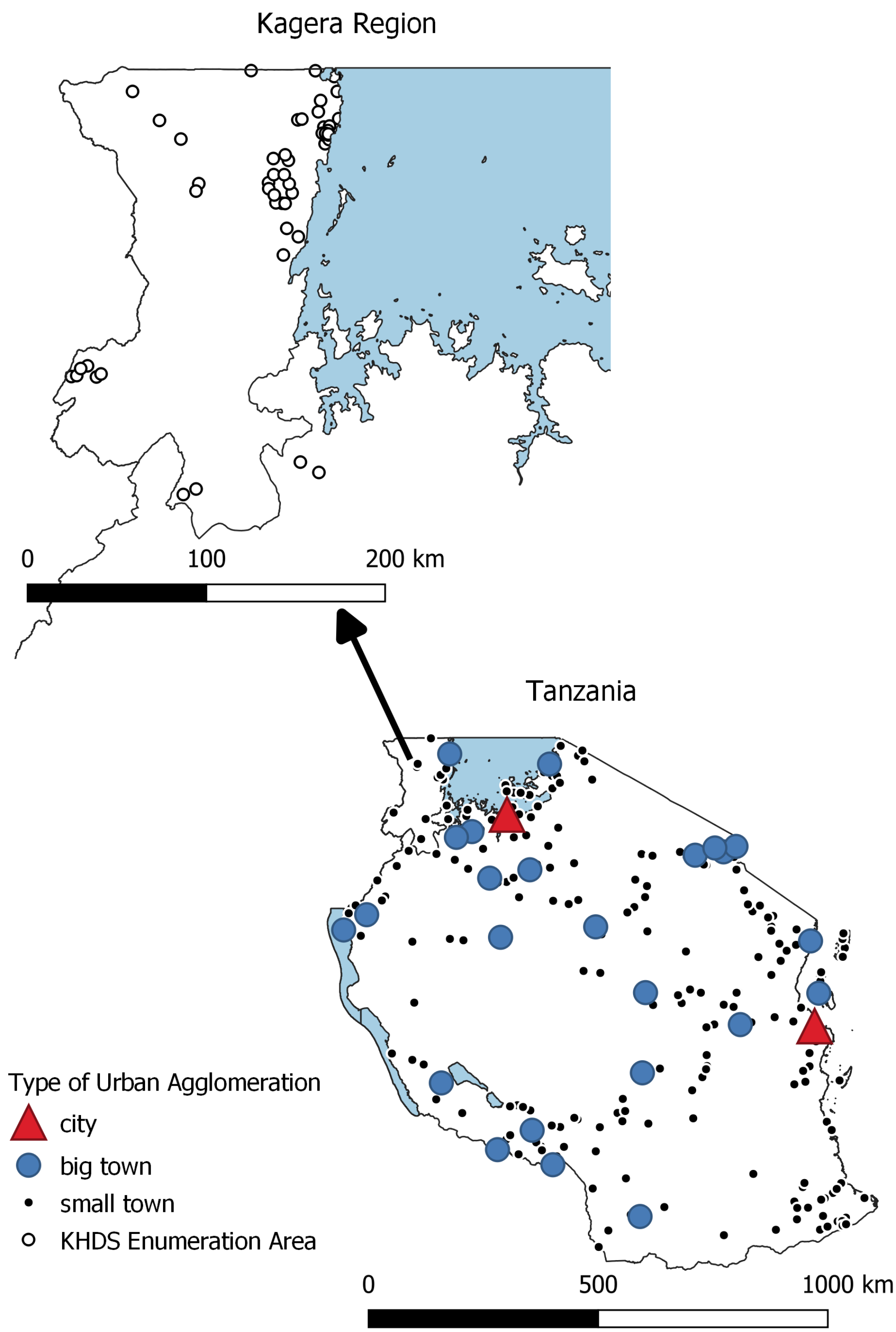


Figure 4: Spatial distribution of urban agglomerations in Tanzania, 2015 (bottom) and KHDS enumeration areas (top)

the census contain all the data we need. The census data gives information on household assets and amenities within the rural and urban areas of each district, but does not identify individual urban agglomerations. Africapolis has population information specific to each urban agglomeration, but has no wealth or amenities data.

The original respondents lived in 47 villages in the Kagera Region in the northwestern part of the country, indicated in the top map in Figure 4. These villages were the rural Enumeration Areas (EAs), als referred to as clusters (4 EAs were urban). We can now ask what the average distance is between the KHDS villages and each of the 249 urban agglomerations of the Africapolis data set, split up by size as before into small towns (10-100k), big towns (100-500k) and cities (>500k). The first panel of Table 8 shows the distance to any urban agglomeration in each of the three categories. We see that the average city, average big town and average small town lies about at the same distance from the EAs.

Of course, migrants are unlikely to go to just any town or city. We know from the previous section that distance is an important consideration. In the next two panels we show the distance to the closest and second closest urban agglomeration. Here we express in numbers what was already obvious from the maps in Figure 4: small towns are, on average, much closer by at 15 km. The average big town lies at 50 km. The closest city, which invariably is Mwanza in our data, lies at an average of 204 km from the KHDS Enumeration Areas, as the bird flies. These differences become more pronounced when we look at the second closest urban agglomeration. For cities this is Dar es Salaam, over 1000 km away on Africa's East coast. The second closest big town lies at 174 km distance, while the second closest small town lies at 29 km distance, on averge. The median values in the next column tell the same story.

There's plenty of variation hiding behind those averages and medians, some of which is illuminated in the last two columns of Table 8. The minimum values shows how close some clusters are to urban areas. One cluster lies in the immediate vicinity (2 km) of Bukoba, so its residents live closer to a big town than a small one. Other Enumeration Areas have themselves been transformed into small towns: the distance between them and a small town has, effectively, been reduced to 0. The border town of Mutukula is a good example. It used to be rural in nature, but has seen a marked increase in people and goods using its border since the construction of a tarmac road has made it accessible throughout the year and at much lower travel times and costs (De Weerdt, 2010). The maximum values inform on the other side of the spectrum and reveal how remote some clusters are. One KHDS cluster lies at a distance of 58 km from the nearest small town and another (different) one at a distance of 166 km from a big town.

Now all elements are in place to show that people's preference for towns over cities, despite their lower economic performance is related to frictions associated with distance. For example in Table 5 the negative effect of distance is over 4 times higher than the positive effect of wealth. This is compounded by the fact that the differences in distance are larger than the differences in wealth. In the census data the wealth index goes up by 0.69 from towns to cities (Table 8), while the nearest city is 1.32 logged kilomtres further than the nearest town (panel 2 of Table 8). In other words the pull effect of higher wealth in cities is much weaker than the discouragement effect of the corresponding increase in distance. We conjecture that that is the reason many people prefer towns over cities.

Who does end up going to they city? Our heterogeneity analysis in Table 6 shows how wealth at destination has a larger pull effect for the non-poor and the educated and how the negative effect of distance on migration choice is attenuated by schooling, but exacerbated by poverty. Such differential frictions would lead to the kind of sorting documented by Hicks et al. (2017) and Young (2013).

6 Concluding discussion

Small towns are on the rise in Tanzania, as they are across much of the African continent. Furthermore their rise is geographically well spread, which means that, increasingly, the average rural migrant will likely be located closer to a small town than to a big one. This shrinking rural-urban distance has a number of important implications for the structural transformation process.

In this paper we have highlighted one such implication by showing the primacy of distance

Table 8: Distance from KHDS villages to urban agglomarations

	distance to any/all (km)			
	mean	**median**	**minimum**	**maximum**
City (>500k)	618	604	143	1,121
Big town (100-500k)	598	655	2	1,183
Small town (10-100k)	668	733	0	1,463
	distance to closest (km)			
	mean	**median**	**minimum**	**maximum**
City (>500k)	206	194	143	285
Big town (100-500k)	55	38	2	166
Small town (10-100k)	16	14	0	58
	distance to second closest (km)			
	mean	**median**	**minimum**	**maximum**
City (>500k)	1,030	1,028	922	1,121
Big town (100-500k)	173	179	56	243
Small town (10-100k)	29	213	6	89

Notes: N=12,201. In this table we link all 47 KHDS villages (rural Enumeration Areas) to all 249 Africapolis urban agglomerations. The urban agglomerations consist of 2 cities (Mwanza and Dar es Salaam), 24 big towns with a population over 100,000 according to Africapolis and 223 small towns with a population under 100,000 but over 10,000 according to Africapolis. The first panel shows summary statistics for distance of the KHDS village to any urban agglomeration in each of the categories. That means they are taken across 2*47 observations for cities, 24*47 observations for big towns and 223*47 observations for small towns. The second and third panel shows the distance to the closest and second closest urban agglomeration in each category. Here the summary statistics are taken across 47 observations in each category (1 urban agglomeration of each type per rural KHDS village) as a determinant of destination choice for a sample of 2,012 internal migrants originating from the Kagera region of Tanzania. If distance from rural to urban areas is associated with migration friction, then we would expect frictions to rural-urban migration to come down through the rise of small towns. Such rural-urban migration is an important component of structural transformation, so the rise of small towns is not only a consequence of this process, but could actually speed it up.

This paper did not try to uncover why distance plays such an important role, but we can get some insights in this from a study of in-depth life histories with 75 respondents from the KHDS survey (Ingelaere et al. 2018). This study confirms that distance plays a central role in the migrant's destination choice and uncovers various different layers that underlie the relevance of distance. The importance of distance is mentioned in relationship to, among other things maintaining ties with the home community, the ability to return home when things go wrong, the socio-cultural affinity with the destination, transport costs and so forth.

We end by noting two avenues for future research that we deem particularly promising. The first is an insight that arose from the qualitative work mentioned in the previous paragraph. This study highlights the difficultly and the importance of the first move. It is difficult because it is often a step in the dark that prospective migrants need to undertake with little preparation and before all the right elements (finances, skills, networks and the like) are in place to ensure that the move will be successful. It often comes with many risks and hardships. It is important because it sets in motion a virtuous circle of physical and economic mobility. In this sense we should not just judge the value of small towns as points of final destinations, but also as enablers of a first move that builds networks, financial resources and human capital potenitally (but not necessarily) leading to further migration - and in particular, further migration that would not have been possible without the intermediary step. With small towns more easily accessible rural dwellers will become more physically mobile, which will open opportunities to make live improving choices. While the importance of transit migration has been highlighted by Artuc and Ozden (2018) in the context of international migration, such insights have not, to the best of our knowledge, made it to the literature on internal migration and urbanisation in Africa. Secondly, there are good reasons to believe other frictions, for example related to the flow of goods, services and information between urban and rural areas will also come down with the emergence of small towns.

While studies like Gibson et al. (201è) and Dorosh and Thurlow (2012) have studied how urban growth in large versus small towns affects rural poverty reduction, very little is known on the exact mechanisms through which this happens.

References

Abadie, Alberto, Susan Athey, Guido Imbens and Jeffrey Wooldridge. 2017. When Should You Adjust Standard Errors for Clustering? NBER Working Paper No. 24003

Anand, Sudhir, and Ravi, Kanbur, 1985. Poverty under the Kuznets Process, Economic Journal, 95(380a): 42-50.

Artuc, Erhan and Caglar Ozden. 2018. Transit Migration: all roads lead to America. Economic Journal 128(July):F306–F334

Baird, Sarah, Graig McIntosh and Berk Ozler. 2013. The regressive demands of demand-driven development. Journal of Public Economics 106:27-41.

Behrens, Kristian, and Alain Pholo, Bala, 2013, Do Rent-Seeking and Interregional Transfers Contribute to Urban Primacy in Sub-Saharan Africa? Papers in Regional Science: 92-1: 163-195.

Beegle, K., J., De Weerdt, and S., Dercon, 2011, Migration and Economic Mobility in Tanzania: Evidence from a Tracking Survey, Review of Economics and Statistics, 93-3: 1010-1033.

Bryan, G., Chowdhury S. and Mobarak A. 2014. Underinvestment in a Profitable Technology: The Case of Seasonal Migration in Bangladesh, Econometrica 82(5): 1671–1748

Caeyers, Bet, Joachim De Weerdt and Neil Chalmers. 2012. Improving Consumption Measurement and other Survey Data through CAPI: Evidence from a Randomized Experiment. Journal of Development Economics 98:19–33.

Christiaensen, L., J. De Weerdt, and Y. Todo, 2013. Urbanization and poverty reduction: the role of rural diversification and secondary towns," Agricultural Economics, 44(4-5):435-447.

Christiaensen, Luc, Joachim De Weerdt and Ravi Kanbur. 2019. Decomposing the contribution of migration to poverty reduction: methodology and application to Tanzania. Applied Economics Letters 26(12):978-982. DOI: 10.1080/13504851.2018.1527436

De Weerdt, Joachim. 2010. Moving out of Poverty in Tanzania: Evidence from Kagera. Journal of Development Studies 46(2): 331-349.

De Weerdt, Joachim and Kalle Hirvonen. 2016. Risk Sharing and Internal Migration. Economic Development and Cultural Change 65(1):63-86.

Dorosh, Paul, and James, Thurlow, 2012. Can Cities or Towns Drive African Development? Economy-wide Analysis for Ethiopia and Uganda, UNU-WIDER Working Paper 2012/50: Helsinki.

Dustmann, C., and A. Okatenko. 2014. "Out-migration, Wealth Constraints, and the Quality of Local Amenities." Journal of Development Economics 110: 52–63.

Fafchamps, Marcel and Forhad Shilpi. 2013. Determinants of the Choice of Migration Destination. Oxford Bulletin of Economics and Statistics, 75(3): 388-409.

Fields, Gary, 2005. A Welfare Economic Analysis of Labor-Market Policies in the Harris-Todaro Model. Journal of Development Economics, 76(1): 127-46.

Gibson, John, Gaurav Datt, Rinku Murgai and Martin Ravallion. 2017. For India's Rural Poor, Growing Towns Matter More Than Growing Cities. World Development 98(2017):413-429.

Giles, John and Kyeongwon Yoo. 2007. Precautionary behavior, migrant networks, and household consumption decisions: An empirical analysis using household panel data from rural China, Review of Economics and Statistics 89(3):534-551.

Gollin, D., D., Lagakos, M., Waugh, 2014, The Agricultural Productivity Gap, The Quarterly Journal of Economics, 129-2: 939-993.

Gollin, Douglas, Martina Kirchberger and David Lagakos. 2017. In search of a spatial equilibrium in the developing world. NBER working paper 23916.

Henderson, J. Vernon. 2003. The Urbanization process and Economic Growth: The So-What Question, Journal of Economic Growth, 8: 47-71.

Hicks, Joan, Marieke Kleemans, Nicholas Li, Edward Miguel. 2017. Reevaluating agricultural productivity gaps with longitudinal microdata. NBER Working Paper 23253, Cambridge, MA.

Hirvonen, Kalle. 2016. Temperature Changes, Household Consumption, and Internal Migration: Evidence from Tanzania. American Journal of Agricultural Economics 98(4):1230–1249.

Hirvonen, Kalle and Bie Lilleør, Helene. 2015. Going Back Home: Internal Return Migration in Rural Tanzania. World Development 70:186-202.

Ingelaere Bert, Luc Christiaensen, Joachim De Weerdt and Ravi Kanbur. 2018. Why Secondary Towns Can Be Important for Poverty Reduction – A Migrant Perspective. World Development 105:273-282.

Kanbur, Ravi, Luc Christiaensen and Joachim De Weerdt. 2019. Where to Create Jobs to Reduce Poverty: Cities or Towns? Journal of Economic Inequality (forthcoming).

Kinnan, Cynthia, Shing-Yi Wang and Yongxiang Wang. 2016. Access to Migration for Rural Households. Mimeo, Northwestern University.

Lanjouw, P. and Marra M. 2018. Urban poverty across the spectrum of Vietnam's towns and cities. World Development 110(2018):295-306.

McKenzie, David, John Gibson and Steven Stillman. 2010. How Important Is Selection? Experimental vs. Non-Experimental Measures of the Income Gains from Migration. Journal of the European Economic Association 8(4):913–945.

Minnesota Population Center. 2014. Integrated Public Use Microdata Series, International: Version 6.3 [Machine-readable database]. Minneapolis: University of Minnesota.

Moriconi-Ebrard, F., D. Harre and P. Heinrigs (2016), Urbanisation Dynamics in West Africa 1950–2010: Africapolis I, 2015 Update, West African Studies, OECD Publishing, Paris, https://doi.org/10.1787/9789264252233-en.

Morten, Melanie. 2019. Temporary Migration and Endogenous Risk Sharing in Village India. Journal of Political Economy. Forthcoming doi10.1086/700763.

Poncet, Sara, 2006. Provincial Migration Dynamics in China: Borders, Costs and Economic Motivations. Regional Science and Urban Economics, 36: 385-398.

Ravallion, Martin, 2002, On the Urbanization of Poverty, Journal of Development Economics, 68(2), 435-442.

Ravallion, Martin, Shaohua Chen and Prem Sangraula, 2007. New Evidence on the Urbanization of Global Poverty, Population and Development Review, 33(4): 667-701.

Wenban-Smith, H. and Ambroz, A. 2014. Urbanisation in Tanzania. IGC Working Paper E-40104-TZA-1/2/3, International Growth Centre.

Young, Alwyn. 2013. Inequality, the Urban-Rural Gap and Migration. Quarterly Journal of Economics 128(4):1727-1785.

Zhang, Junfu, and Zhong Zhao, 2013. Measuring the Income-Distance Trade-Off for Rural-Urban Migrants in China. IZA Discussion Paper 7160.