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RURAL LABOUR PRODUCTIVITY AND URBANISATION IN SUB-SAHARAN AFRICA

By

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RURAL LABOUR PRODUCTIVITY AND URBANISATION IN SUB-SAHARAN AFRICA

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ABSTRACT

Over the last few decades, Sub-Saharan Africa has been urbanizing at an unprecedented rate. While there is evidence that this has led to rural-to-urban migration, real structural transformation has not taken place: the majority of Africa's poor people still live in rural areas and are primarily engaged in low productivity agriculture. This paper addresses the link between urbanisation and rural labour productivity. It is hypothesised that urbanisation stimulates both the demand for and supply of more working hours outside of agriculture. The proximity of an urban agglomeration induces a demand for diversified employment, and the highly seasonal agricultural calendar offers space for off-farm employment. By combining panel data on employment and night light data as a proxy for urbanisation, this paper explores the spatial and temporal link between rural labour supply and the proximity of agglomerations for Sub-Saharan Africa for the period 2008-2014. Not only will it look at the effect of urbanisation on the number of hours supplied, but it will also provide insight in how these hours are allocated sector wise. Using LSMS-ISA employment data on a panel of around 50 000 individuals from six different African countries, allows us to shift the focus from sector productivity to individual level productivity, as well as account for individual fixed effects. Nightlight data have shown to be a good proxy for urbanisation and are particularly interesting for Sub-Saharan Africa, where urbanisation statistics lag behind reality. Nightlights provide us with fine-grained urbanisation information with which we can investigate the role of the emerging small towns (which are mushrooming up all over Africa) on the rural population. Our analysis has the potential to inform the formulation of labour policies as well as urban planning that can maximize the positive effects of African urbanisation on the rural poor.

1.0 INTRODUCTION

Structural transformation in sub-Saharan Africa has been the subject of much debate. Macro-economic analysis show that the potential for economic growth stemming from reallocation of labour out of agriculture into services and manufacturing is substantial, given the large productivity gap between agriculture and the non-agricultural sector (Gollin, Lagakos, & Waugh, 2014; McMillan, Rodrik, & Verduzco-Gallo, 2014). Puzzling is the fact that despite the large productivity gains that would come from such a move, structural transformation is not taking place.

Research into the explanations of why labour is not moving out of agriculture on a significant scale, broadly focus on two explanations: whether the agricultural productivity gap arises due to measurement error, or whether large movements out of agriculture are inhibited by significant exit barriers or selection (Adamopoulos & Restuccia, 2014; Beegle, De Weerdt, & Dercon, 2011; Bryan, Chowdhury, & Mobarak, 2014; Hall & Jones, 1999; Herrendorf & Schoellman, 2015; McCullough, 2017; Miguel & Hamory, 2009; Sen, 2006). Of particular interest are the studies nuancing findings on the large agricultural productivity gap as uncovered with macro-data. As such do Miguel and Hamory (2009) show that selection into migration due to differences in ability can explain a great deal of labour movements in Kenya. McCullough (2017) uses micro data on individual labour supply to provide evidence that the measured agricultural productivity gap of Gollin et al. (2014) shrinks in half when taking into account differences in individual hours supplied.

If agriculture is not as unproductive as macro-economists claim it to be, economic growth stemming from structural transformation, as explained by the theory of Lewis (1955), is limited. How then can economic growth in sub-Saharan Africa be materialised? Scholars such as Barrett, Christiaensen, Sheahan, and Shimeles (2017) Barrett, Reardon, and Webb (2001) and Steel and van Lindert (2017) have shown the potential of income diversification and nonfarm activities for economic development of rural Africa. McCullough (2017) and other scholars such as Nagler and Naudé (2013), Wiggins (2000)and Yumkella, Kormawa, Roepstorff, and Hawkins (2011) provide evidence of a strong growth linkage between agriculture and nonfarm activities, which can also stimulate rural development in sub-Saharan Africa.

This paper provides evidence that one such stimulator of rural economic growth through its positive effects on income diversification, nonfarm employment and labour productivity, is growth in nearby towns. Urbanisation in sub-Saharan Africa is increasing in an unprecedented manner, yet much of it is still poorly understood and happening off the radar. One of the reasons why investigations on urbanisation dynamics in sub-Saharan Africa have remained scarce is the lack of reliable and regularly available statistical data. International comparison between urbanisation statistics is often made difficult by substantial definitional differences concerning urban status (Satterthwaite, 2010).

The rapid urbanisation in sub-Saharan Africa has also informed analyses on the process of structural transformation, or lack thereof (de Brauw et al., 2014; Henderson & Kriticos, 2017; McMillan, Rodrik, & Verduzco-Gallo, 2014). Many of these scholars' touch upon the 'urbanisation without growth' phenomenon observed particularly in sub-Saharan African, while others try to dismiss these claims (Fay & Opal, 2000; Fox, 2012; Gollin et al., 2015; Jedwab, 2013; Onjala & K'Akumu, 2016). Certain is that the unfolding urbanisation patterns in sub-Saharan Africa and its links with development are puzzling from a classical economic point of view: urbanisation in sub-Saharan Africa has seemingly not been preceded by economic growth or industrialisation.

This paper uses the novel combination of micro data on labour productivity and night light data as a proxy for urbanisation into a panel dataset that investigates the impact of urbanisation on labour patterns in rural areas in six[1] sub-Sahara African countries. It finds evidence for a response of labour supply and income diversification to an increase in urbanisation. It is particularly nearby urbanisation that has a significant effect on labour supply. This adds evidence to the growing literature on the importance of small towns for rural development and poverty alleviation (Christiaensen, De Weerdt, & Kanbur, 2017; Gibson, Datt, Murgai, & Ravallion, 2017; Ingelaere, Christiaensen, De Weerdt, & Kanbur, 2018). Further does it provide evidence that urbanisation stimulates rural income

[1] This version currently only looks at Ethiopia and Malawi

diversification, and thus rural labour productivity. This casts doubts on the premise of classical economic theory that economic growth coming from structural transformation (labour moving out of the least productive sector) constitutes as the major force for development in sub-Saharan Africa (Lewis, 1955; Rostow, 1960). Rather does it provide evidence that growth linkages between the agricultural and the non-agricultural sector are present, which shows that the Mellor-Johnson thesis is still relevant today (Dercon & Gollin, 2014).

This paper taps into two of the most challenging policy questions of today for sub-Saharan Africa. The majority of Africa's poor still live in rural areas and are predominantly employed in agriculture. Understanding livelihood strategies of the rural population is key in identifying proper policies to battle poverty. Focusing on the rural and thus predominantly agriculture, is still the most effective in reducing poverty (Christiaensen, 2018). At the same time does the steady urbanisation of sub-Saharan Africa require immediate policy attention. When urbanisation is poorly understood, it risks to be poorly managed and give rise to significant congestion costs, climate effects and rise in inequality (McGranahan & Satterthwaite, 2014). Mapping and understanding urbanisation is thus key in building effective institutional and policy frameworks to guarantee that urbanisation is advantageous for the economy and the society (Bloom, Canning, Fink, Khanna, & Salyer, 2010).

2.0 BACKGROUND

Household surveys have shown that rural labour markets in developing countries are characterized by two pervasive facts. The first is that agricultural workers work surprisingly few hours per year. For example, McCullough (2017) looks at LSMS-ISA data from four African countries and finds 700 hours worked per agricultural worker, per year, which would be equivalent to 88 working days of 8 hours work.

The second is that agriculture requires labour intermittently throughout the agricultural season. For example, Arthi, Beegle, De Weerdt, and Palacios-López (2018) show that both at the extensive margin (who works on the farm) and at the intensive margin (how much they work), there is much irregularity.

These two stylized facts have a number of important implications. First, agriculture is not an intrinsically unproductive sector; at least not once we consider agricultural productivity as output per hour worked. Second, despite high per-hour-worked productivity, the total number of hours worked reveal significant levels of underemployment in agriculture. In short, the agricultural sector suffers much less from low productivity than it does from underemployment.

Off-farm activities present one opportunity to supply more hours of labour per year, but the supply of labour is restricted by the irregularity of the agricultural schedule. The challenge is for the labour demand to fit that schedule. As such do Nagler and Naudé (2014) show with a time series analysis on the LSMS-ISA data for six African countries that a significant part of non-farm entrepreneurship serves to complement seasonal agricultural labour. One source of demand for labour from outside agriculture could be in nearby urban centres. The pull factor of nearby urbanisation for nonfarm wage employment has already been shown by Fafchamps and Shilpi (2003) for the case of Nepal, and urbanisation as a stimulator for income diversification and off-farm employment has been mentioned by (Calì & Menon, 2013; Christiaensen, 2013; Nagler & Naudé, 2014). By linking urban growth data to rural household survey data, we will investigate empirically how urban growth is affecting local labour markets. The basic premise is that growth in a nearby town provides opportunities to supplement farm activities with off-farm work – opportunities that would not exist without the existence of the town.

3.0 DATA DESCRIPTION

3.1 LSMS-ISA

To look at different forms of labour supply, a panel dataset will be constructed from the World Bank Living Standards Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA) dataset. The LSMS-ISA project is implemented by the World Bank Group and aims at, in collaboration with national statistics offices, developing a database with novel and detailed statistics on household variables, with a particular focus on agriculture. Currently, it runs in eight sub-Saharan countries: Burkina Faso, Ethiopia, Malawi, Mali, Niger, Nigeria, Tanzania and Uganda.

The datasets are nationally representative and have both rural and urban Enumeration Areas (EAs) in their sample. These EAs consist of both farming as well as non-farming households. The dataset is unique in its kind as it provides us with highly detailed information on household farming and labour involved, labour market participation and household non-farm enterprises. It generally consists of three questionnaires: a household questionnaire, an agricultural questionnaire and a community questionnaire. Most importantly are the survey data georeferenced at the EA level, which allows us to exploit spatial characteristics of the data.

The rural/urban status of the EAs in the LSMS-ISA dataset is derived from national definitions, often those applied in national censuses. Depending on the country, this definition applies a population size, settlement type or other criteria. As the criteria of these definitions often differ significantly, international comparability is limited (ILO, 2018; Satterthwaite, 2010). For this reason, rural/urban classification will be made based on a continent-wide definition of night light thresholds. This will be explained in the next section.

In this version, we focus our analysis on Ethiopia and Malawi due to the comparability of the questionnaires and time period. The final version of the analysis will include individuals from four other LSMS-ISA countries: Niger, Nigeria, Tanzania and Uganda.

The current dataset comprises of the first wave (2010-2011) and the second wave (2013) of the Third Integrated Household Survey of Malawi, and the first wave (2011-2012) and the second wave (2013-2014) of the (Rural) Socioeconomic Survey of Ethiopia. The characteristics of the sample used in the analysis below are described in Table 1. The analysis sample consists of those individuals that are aged 15 or above and reside in rural areas as defined with a night light definition. We only retained the individuals that did not move between the two waves. Also, newcomers to the household in wave 2 are discarded.

Table 1: LSMS-ISA Dataset characteristics

	Ethiopia		Malawi	
	2011-2012	2013-2014	2010-2011	2013
Number of individuals in sample	15374	15374	9917	9917
Number of individuals aged≥15	7932	8653	5042	5858
Number of households	3595	3595	2153	2153
Average household size	5.46	5.46	5.71	5.71
Average household size aged≤5	0.19	0.70	1.00	0.38
Average household size 5<aged≤15	1.99	2.06	1.97	2.07
Average household size aged>15	3.47	2.86	2.74	3.26
Number of households with at least one non-farm enterprise	986	1177	388	617
Number of individuals aged≥15 that performed any wage labour over the last year	492	459	376	391
Average hours worked in agriculture over the last week	13.94	12.48	7.73	7.42

The LSMS-ISA dataset is used to construct variables on individual labour supply in three main sectors: agriculture, non-farm household enterprises and wage labour. The constructed variables, their type and the linked survey question can be found in Table 2.

Table 2: Constructed Labour Variables

	Type	Corresponding survey question	
		Ethiopia	Malawi
Individual labour supply			
Nonfarm enterprise	Dummy	Over the past 12 months, has anyone in this household .. [Answered yes to any of the questions on non-farm enterprise as detailed in table A in appendix]	Over the past 12 months, has anyone in this household .. [Answered yes to any of the questions on non-farm enterprise as detailed in table A in appendix]
Nonfarm enterprise worker	Dummy	Which household members worked in this non-farm enterprise in the last 12 months? (up to 5 per household)	During the last month of operation, [# member] that worked for the NFE (up to 4 members per household)
Wage employment	Dummy	At any time over the last 12 months, were you employed for a job, including casual/part-time labour, for a wage, salary, commission or any payment in kind, excluding temporary, for anyone who is not a member of your household?	At any time over the last 12 months, were you employed for a wage, salary, commission or any payment in kind, excluding ganyu, for anyone who is not a member of your household?
Hours worked in agriculture in the last week	Continuous, truncated at 84 (max 12h/day)	How many hours in the last seven days did you spend on household agricultural activities (including livestock and fishing-related activities) whether for sale or for household use?	How many hours in the last seven days did you spend on household agricultural activities (including livestock and fishing-related activities) whether for sale or for household food?
Hours worked outside of agriculture in the last week	Continuous, truncated at 84 (max 12h/day)	How many hours in the last seven days did you run or help with any kind of non-agricultural or non-fishing household business, big or small, for yourself or for the household?	How many hours in the last seven days did you run or do any kind of non-agricultural or non-fishing household business, big or small, for yourself? + How many hours in the last seven days did you help in any

			of the household's non-agricultural or non-fishing household businesses, if any?
Hours worked in non-farm enterprise over the last year*			
Hours worked in wage employment over the last year*			
Hours worked in agriculture over the last year*			
Individual labour productivity			
Per hour productivity in non-farm enterprise*			
Per hour productivity in wage labour*			
Per hour productivity in agriculture*			

***Variable not yet included in the analysis**

3.2 NIGHT TIME LIGHTS

3.2.1 Background

The use of Night Time Lights (NTL) to study socio-economic development is not new. Since the digitalization of Nighttime Lights datasets of the Defense Meteorological Satellite Program Operational Line Scanner (DMSP/OLS) in 1992, studies in a broad range of disciplines using these datasets have skyrocketed (Doll, 2008; Huang, Yang, Gao, Yang, & Zhao, 2014).

A significant part of these studies use NTL to study socioeconomic development or urbanization at the global, regional or national level (Bennett & Smith, 2017; Doll, 2008; Huang et al., 2014). Some investigate the statistical relationship between NTL emissions and socio-economic variables such as GDP, population density or built-up area, and it has been shown that in general NTL correlates well with socio-economic activity (Bennett & Smith, 2017; Briggs, Gulliver, Fecht, & Vienneau, 2007; Doll, Muller, & Morley, 2006; Sutton, Roberts, Elvidge, & Baugh, 2001; Zhang & Seto, 2013). The first studies proving the correlation between NTL and economic activity, population, electric power consumption and urban extent, date from already two decades ago (Elvidge, Baugh, Kihn, Kroehl, & Davis, 1997; C. D. Elvidge et al., 1997; L.Imhoff, Lawrence, Stutzer, & Elvidge, 1997). More recent studies have used NTL time series to investigate its power in explaining temporal changes in these variables (Bennett & Smith, 2017; Henderson, Storeygard, & Weil, 2012; Small & Elvidge, 2013; Yi et al., 2014). Other studies use NTL as a proxy for socio-economic variables of which reliable statistical data is lacking (Donaldson & Storeygard, 2016; Huang et al., 2014). These studies have been instrumental in uncovering distributional and temporal patterns of a range of variables identifying urban dynamics, such as urban boundaries, intercity dynamics, built-up area and population dynamics, both at one point in time as over time (Bennett & Smith, 2017; Doll, 2008; Huang et al., 2014; Ma et al., 2015; Zhang & Seto, 2011).

The bulk of the studies using NTL data to investigate urbanization dynamics are regionally skewed towards Asia and the US, with China leading the list (Bennett & Smith, 2017). In the last few years, several studies on Latin America have emerged (Álvarez-Berríos, Parés-Ramos, & Aide, 2013; Parés-Ramos, Álvarez-Berríos, & Aide, 2013; Rodriguez Lopez, Heider, & Scheffran, 2017). Studies using NTL in the context of sub-Saharan Africa are rather scarce. The region is featured in studies investigation the link between economic growth or urbanization and NTL on a global scale (Henderson et al., 2012; Zhang & Seto, 2013), and a few recent studies use NTL as a proxy for economic activity for one or more countries in Africa (Michalopoulos & Papaioannou, 2013, 2014; Rohner, Thoenig, & Zilibotti, 2013; Storeygard, 2016). To our knowledge, only three studies focusing specifically on urbanization and Nighttime Light in the African context (Binswanger-Mkhize & Savastano, 2017; Chen & Nordhaus, 2015; Savory et al., 2017).

The Nighttime Lights datasets are made available by the National Oceanic and Atmospheric Administration/National Geophysical Data Center (NOAA/NGDC). The NTL products come from two main sources. The oldest and most popular is the Version 4 Nighttime Lights Time Series Dataset from the Defense Meteorological Satellite Program Operational Line Scanner (DMSP-OLS). It was launched in the 1960s to detect cloud coverage, but since its digitalization in 1992, the nighttime images from the DMSP/OLS have become widely popular as an instrument to investigate anthropogenic activity (Doll, 2008). The latest and last Version 4 spans the period 1992-2013 and contains three different datasets collected from nine satellites. These three composites are a cloud free coverage, nighttime stable lights and average visible data. They differ in the extent of what they filter out and what they measure. The newest set of data comes from the Visible Infrared Imager Radiometer Suite (VIIRS) Day/Night Band (DNB) of the National Polar-Orbiting Operational Environmental Satellite System (NPOESS). It was launched in 2011 by NASA and NOAA and contains multiple significant improvements on the DMSP/OLS. Three cloud free products have been produced for 2015; a raw cloud-free composite, an outlier-removed cloud-free composite and a Night-Time Lights dataset (Elvidge, Baugh, Zhizhin, Hsu, & Ghosh, 2017). Chen and Nordhaus (2015) test the ability of the VIIRS data to serve as a proxy for population and economic output in Africa and find that it has the potential to improve the predictions of the DMSP/OLS datasets on socio-economic dynamics in Sub-Saharan Africa. The VIIRS data also have the potential to mitigate possible biases from DMSP/OLS data when using NTL as a proxy for urbanization in developing countries (Zhang & Seto, 2013).

Currently the DMSP/OLS datasets are still the most used due to its availability of long time series data and the limited availability of VIIRS processed composites. However, the improvements in the quality of the data compared with DMSP/OLS, the increase in products available in the near future and the development of intercalibration methods between the two sets of data (Li, Li, Xu, & Wu, 2017), have the potential to signal a new era in research using nighttime lights. More information on the datasets and the technicalities of the satellites can be found on NOAA/NGDCs website[2] and in (Doll, 2008; Elvidge et al., 2017; Huang et al., 2014).

Using DMSP/OLS datasets to study socio-economic patterns however come with widely recognized limitations. The most serious setback for time series analyses is the lack of inter- and intercalibration between different satellites. This is a potential serious problem, as it has been shown that the amount of NTL picked up by two different satellites in the same year can differ by as much as 10%. This is problematic when studying temporal changes over a period in which night time light is recorded by multiple satellites. Different intercalibration methods have been developed to solve this issue (Huang et al., 2014; Small & Elvidge, 2013). Other common setbacks of NTL data are the presence of blooming, overglow, and the oversaturation of pixels. Blooming and overglow are the

[2] https://ngdc.noaa.gov/eog/index.html

phenomena that nighttime light is recorded where there is actually no light, due to reflection of for example lakes (blooming), or the extension of nighttime lights from lighted pixels into the periphery (overglow). Oversaturation of pixels stems from the fact that the maximum DN value for light intensity is set at 63 which causes the DN values of very bright pixels to be truncated on top, with the consequence of possible loss of information (Huang et al., 2014; Zhang & Seto, 2011).

3.2.2 Used NTL dataset

Until recently, no paper documenting or dealing with these issues in the case of sub-Saharan Africa was available. Savory et al. (2017) however, have developed and made freely available an intercalibrated dataset for Africa for the period 2000-2013 based on the Stable Lights composites of the DMSP/OLS dataset. We chose to use this dataset for our analysis for multiple reasons. First of all because with the use of the invariant region and quadratic regression method (IRQR) and Gaussian Process Modelling, it was able to develop a database that smoothed out the discrepancies between different satellite signals. This discrepancy was particularly present between satellite F16 and F18, covering the period 2004-2009 and 2010-2013 respectively, which is the time period of our analysis. Secondly because next to intercalibration, it also removes NTL stemming from gas flares and corrects for blooming by masking the datasets with Water Bodies datasets. Thirdly was not only the dataset especially developed for studying temporal urbanization dynamics in Africa, its capacity to do so was also tested by calculating correlations of the new dataset with GDP and urban population. It is shown that for our sample, the dataset performs particularly well with correlations at the country level with urban population all being 0.9 or above.

This dataset does not correct for overglow or saturation of pixels. Overglow will be dealt with by using a thresholding method, which will be further elaborated upon below. Saturation of pixels is not a serious limitation in the case of Africa, as less than 1% of the dataset recorded a light intensity with DN value 63 for 2013. It is however the opposite, the failure to detect certain agglomeration dynamics due to low electrification rates, that is a potential serious bias in developing countries and thus sub-Saharan Africa. This among other setbacks, have led scholars such as Bennett and Smith (2017); Zhang and Seto (2013) to warn against the use of NTL data to study socio-economic development in developing countries. The fact that this omission is likely to not be random should be kept in mind when interpreting the results. The limitations section will deal with this in more detail.

Keeping this potential bias in mind, NTL nevertheless provides a huge potential for studying urbanization in sub-Saharan Africa that despite the large interest from scholars, remains relatively poorly understood. As mentioned by Álvarez-Berríos et al. (2013), Bennett and Smith (2017) and Donaldson and Storeygard (2016), NTL can prove especially useful for studying urbanization in countries for which official reliable statistics are lacking. The potential is fourfold. First of all does it eliminate the reliability on national statistics that are often only sporadically available, of questionable reliability and lag behind reality. Next is international comparability possible due to the universal coverage of the satellite data. This is often not the case for urban/rural definitions that are decided upon nationally and are hard to interpret and compare, even in one national context (Allen, 2018). Thirdly does the availability of NTL data for a long time period create the opportunity to look at temporal changes in urbanization dynamics, instead of the snapshot pictures that are derived from statistical data gathered at one point in time. Finally does the high spatial granularity (30 arc-second image grid) allow us to investigate urbanization dynamics on a subnational level.

3.2.3 Constructed urbanisation variables

Despite the huge amount of studies using NTL to study urbanization dynamics, Bennett and Smith (2017) mention that the relationship between NTL and urbanization is context dependent, which limits the applicability of the methodologies used in the many studies on urbanization dynamics in the US, China and India to the African context. For example the extent to which agricultural area is lighted differs significantly between countries, which shows that no consensus on threshold exist between contexts (Ma et al., 2015; Small & Elvidge, 2013).

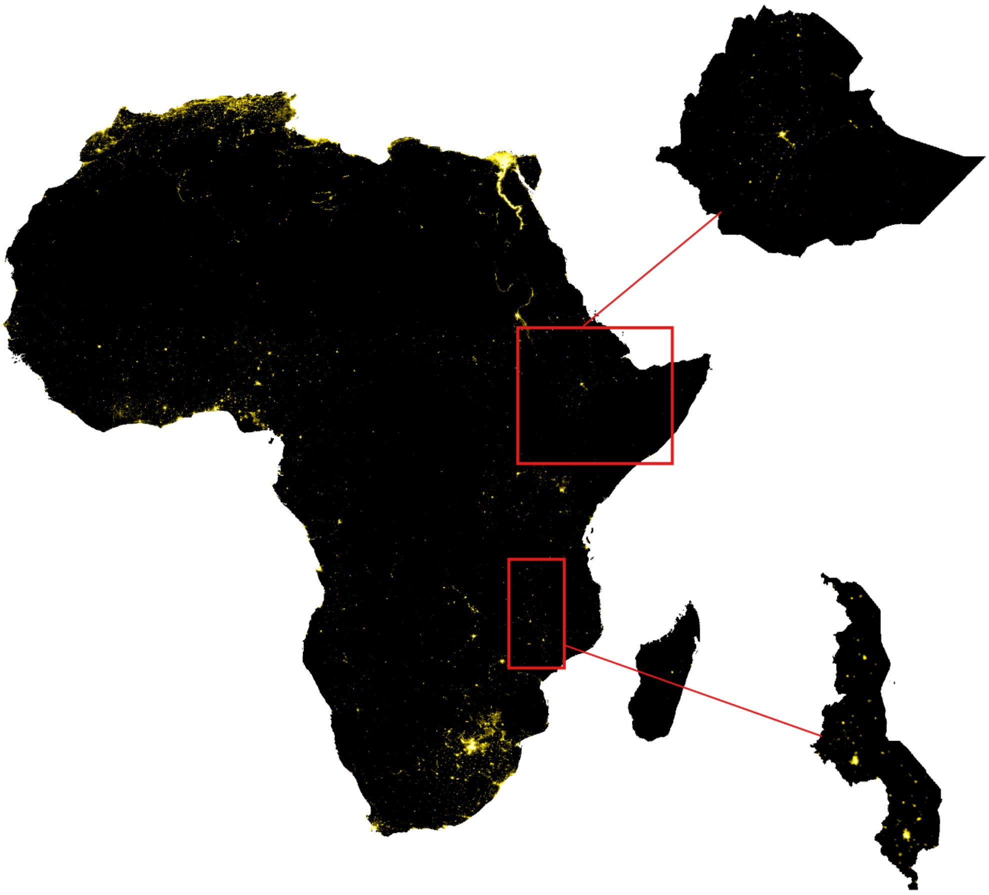
So while the potential added value of NTL for studying urbanization in SSA is huge, especially given the GP calibrated dataset of Savory et al. (2017), the challenge lies in identifying a proper estimation strategy that is best tailored to the African context.

By studying intensively and qualitatively the intercalibrated NTL datasets of Savory et al. (2017), we have developed two main variables to capture urbanisation dynamics in sub-Saharan Africa. The manipulations where performed on the rasterfiles that are made freely available[3]. For each year of survey data, the according NTL rasterfile was used as reference[4]. It should be mentioned that surface where any NTL was detected in sub-Saharan Africa is much smaller than in developed countries. Figure 1 shows NTL on the African continent as of 2013. We see that, rather than consisting of continuously lit surface, Africa mainly exists of a dark surface with some distinct light clusters. These light hubs are proven to be highly correlated with urbanisation (Savory et al., 2017).

[3] https://geodata.globalhealthapp.net/

[4] For Niger, the second wave of the LSMS-ISA survey was held in 2014. Due to the NTL time series database ending in 2013, 2013 was used as the reference year. For Ethiopia and Uganda, the second and forth wave respectively were held in 2013-2014. Also for these waves, the 2013 rasterfiles were used as reference.

Figure 1: *Night Time Lights in Africa in 2013, with a focus on Ethiopia and Malawi*



Although Savory et al. (2017) chose to forgo thresholding due to its “uncertain efficacy” (p. 6), qualitative exploration of the data showed that the unfiltered dataset exhibit ‘noise’, due to overglow and other sources of nightlight that are not directly related to urbanisation, severe enough to threaten the validity of the our analysis. For this reason, it was decided to apply a threshold at DN value of 3[5]. The particular cut off value of DN 3 was chosen as it appeared to balance the trade-off between false positives (recorded NTL but no actual agglomeration) and false negatives (no recorded NTL where an actual agglomeration is present). As a consequence, all the EAs that were located in an area with a DN value less than three, were considered rural in our sample. Although some scholars apply relative threshold values based on national range of light intensity, we chose to apply a

[5] Each pixel in the rasterfile is assigned a Digital Number (DN) that measures light intensity, ranging from 0 (no night light) to 63 (maximum light intensity that can be recorded).

continent-wide absolute threshold to assure international comparability. The robustness checks section will provide evidence that the results still stand when different thresholds are applied.

We are now left with multiple clusters that are continuously lit with DN>3. The size of these clusters can range from only one lit pixel, which is approximately 1 km², to very large clusters of more than 1000 km².To make the analysis more intuitive, the remainder of this paper will refer to these light clusters as 'agglomerations'. Table 3 provides descriptive statistics on the agglomerations in the sample for each country and each year.

Table 3: Descriptive statistics on Night Light Clusters

	Ethiopia		Malawi	
	2011-2012	2013-2014	2010-2011	2013
Number of light clusters	237	250	72	87
Total sum of lights	86594.18	96189.36	40781.7	43556.68
Largest sum of lights/cluster	30803	33398	12615	12592
Smallest sum of lights/cluster	3	3	3	3
Average max DN value/cluster	8.70	9.05	10.37	9.77
Average min DN value/cluster	3.34	3.31	3.44	3.29
Total lit area	8657 km²	9468 km²	2917 km²	3278 km²
Percentage lit area of total country area	0.76%	0.83%	2.58%	2.90%

Each pixel in the rasterfile is assigned a Digital Number (DN) that measures light intensity, ranging from 0 (no night light) to 63 (maximum light intensity that can be recorded). The sum of lights is the sum of the light intensity of each pixel that is part of a given light cluster.

Taking a look at the descriptive statistics of Table 3, we can see that both on the extensive and intensive margin, NTL increased between survey waves. As such did both the number of night light clusters and the total lit area, as well as their total sum of lights increased.

3.2.3.1 Sum of Lights Variable

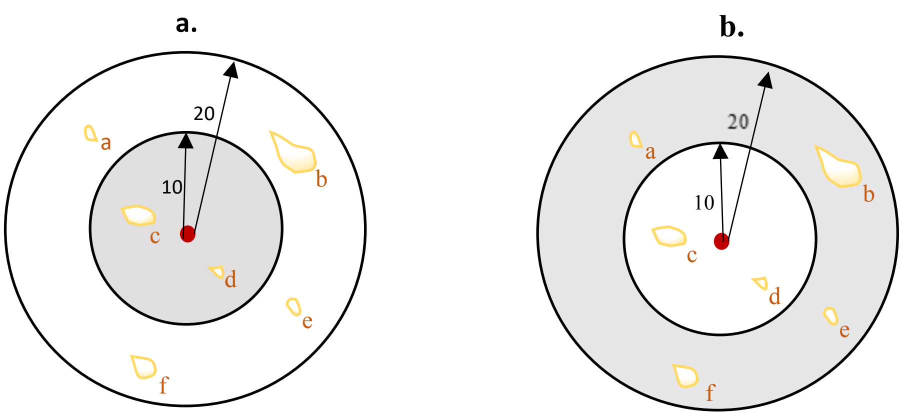
The first variable constructed from the data captures urbanisation by recording the Sum Of Lights (SOL) in a rural EA *i* at time *t* by adding up the sum of lights[6] of each agglomeration located in the area between two concentric circles around the EA *i*:

$$\boldsymbol{SOL_{i,t,a,b}} = \sum\nolimits_{\boldsymbol{a<dist_{i,j,t}\leq b}}^{\boldsymbol{n}} \boldsymbol{sol_{j,t}} \qquad \textbf{(1)}$$

With *a* the radius of the lower limit concentric circle around *i*, *b* the radius of the upper limit concentric circle around *i*, $sol_{j,t}$ the sum of lights of agglomeration *j* at time *t*, and $dist_{i,j,t}$ the distance between EA *i* and the centroid of agglomeration *j*. The summation is conditional on $dist_{i,j}$ laying between the lower and upper radius of the concentric circles around *i*. Figure 2 provides an illustration of this SOL formula.

The Sum Of Lights is a popular measure in literature using NTL to study economic development, as it takes both the size of the lit area as well as the intensity into account (Ghosh et al., 2010; Gibson et al., 2017; Henderson, Squires, Storeygard, & Weil, 2018; Small & Elvidge, 2013). It can thus be thought of as balancing the importance of the intensive margin as well as the extensive margin of urbanisation.

Figure 2: Sum of Lights Urbanisation Variable Illustrated



$SOL_{1,0-10} = sol_c + sol_d$ $\qquad$ $SOL_{1,10-20} = sol_a + sol_b + sol_e + sol_f$

[6] The sum of lights is the sum of the light intensity (expressed as a DN value ranging from 0 to 63) of each pixel that is part of a given light cluster.

Suppose the red dot is an EA with i=1 and the yellow spots are agglomerations surrounding EA_1 at time t, defined by night light clusters. The first concentric circle around $EA_{1,t}$ has a radius of 10 kilometres, while the second concentric circle around it has a radius of 20 kilometres. Suppose we want to calculate the SOL of the area up to 10 kilometres from the EA, and the area surrounding this area up to 20 kilometres from the EA, as indicated by the grey areas in a. and b. The SOL of the grey area in a. would then be $SOL_{1,0-10} = sol_c + sol_d$, and the SOL of the grey area in b. would be $SOL_{1,10-20} = sol_a + sol_b + sol_e + sol_f$.

It is useful to disentangle urbanisation stemming from different concentric circles around a rural area to be able to assess the relative importance of urbanisation happening in areas at different distances from rural areas. In our analysis, we will generally apply the 0-10km, 10-20km, 20-50km and 50-country boundary intervals, as they can be interpreted intuitively. As such does the 0-10km interval captures more or less any location within walking distance, the 10-20km interval any location that can be reached by bike or public transport, the 20-50km interval a distance that demands a longer travel of more or less maximum a day, and the last interval can be seen as containing locations significantly 'far away'.

3.2.3.2 Urban Access Variable

To exploit the continuity of 'urbanness' and the importance of distance to the maximum, we constructed a second measure of urban influence; an Urban Access[7] variable. This Urban Access variable exploits both the magnitude (intensive and extensive) of urbanisation as well as the distance to a certain agglomeration:

$$\boldsymbol{UA_{i,t} = \sum_{j=1}^{n} sol_{j,t} * dist_{i,j,t}^{\alpha}} \qquad \textbf{(2)}$$

With sol_j the sum of lights of agglomeration *j* at time *t*, and $dist_{i,j}$ the distance between EA *i* and the centroid of agglomeration *j*. *α* is a discount factor that weights this distance. The larger *α,* the less urban influence further away agglomerations are assumed to have on a rural area.

[7] Inspiration was derived from the market access variable constructed by Blankespoor, Mesplé-Somps, and Spielvogel (2016)

The choice of *α* is rather intuitive. Suppose we have three agglomerations with sol=50, sol=500 and sol=5000. These values are more or less representative in our sample for a small, a medium and large agglomeration. Setting *α* =-1 would mean that a big agglomeration 1000 km away has the same influence as a medium agglomeration 100 km away, and a small agglomeration just 10 km away. Intuitively, this clearly overestimates the importance of faraway agglomerations. Setting *α* =-2 would mean that a big agglomeration 316 km away has the same influence as a medium agglomeration 31 km away, and a small agglomeration just 10 km away. As for now, *α* =2 seems as a reasonable discount factor. Robustness checks will evaluate the sensitivity of the results to different values of *α*.

3.3 Descriptive analysis

A first exploration of the data clearly indicates that different labour moves over time in rural areas experience different spatial patterns of urbanisation. In Table 4 the demeaned change in SOL in four different concentric circles (doughnuts) around the rural survey areas are calculated for three main sectors of employment: non-farm enterprise, wage labour and agricultural labour. More specifically, it shows the average demeaned change in SOL for four distinct labour choices over time: the individuals who were not active in the particular sector in year 1 and were still not in year 2, those who were not active but became active in year 2, those who were working in the sector in year 1 but not anymore in year 2, and those who were already active in the sector in year 1 and remained active in year 2. By splitting up the change in urbanisation over time in these for different choice groups, we can get a clearer insight in the link between labour supply choices and urbanisation growth.

In general, are the deviations from the average urbanisation trend diminishing with urban growth further away. If we zoom in on the individuals that selected into non-farm enterprise labour where they previously did not supply any hours of labour in this sector, we see that they experienced urban growth in the area within 10 km from their place of residence that is 4.3% higher than the average urbanisation trend for the 10km circle around rural areas for the sample as a whole. For wage labour, this is even 9.3%.

However, this differential effect dissolves quickly with distance from the rural area. Figure 3 explores spatially the link between moving into non-farm enterprise jobs and wage labour respectively, and experienced urbanisation growth. Further do we see that above average urbanisation growth in the 10-20 concentric circle around a rural area, is linked with moving out of non-farm enterprises as well as out of agriculture. This might indicate that substantial urbanisation growth in not too close but not too far agglomerations might stimulate people to get a job in these towns. Lastly are differential urbanisation experiences becoming very small once we look at urbanisation happening at a distance of 50 kilometres and beyond. This could indicate that proximity of urbanisation is an important indicator for influencing labour choices.

Table 4 and **Figure 3** provide a first indication that different kinds of urbanisation drive different labour decisions, and that proximity of agglomerations is possibly an important indicator for labour choice. The following section will explore empirically the link between urbanisation and rural labour supply.

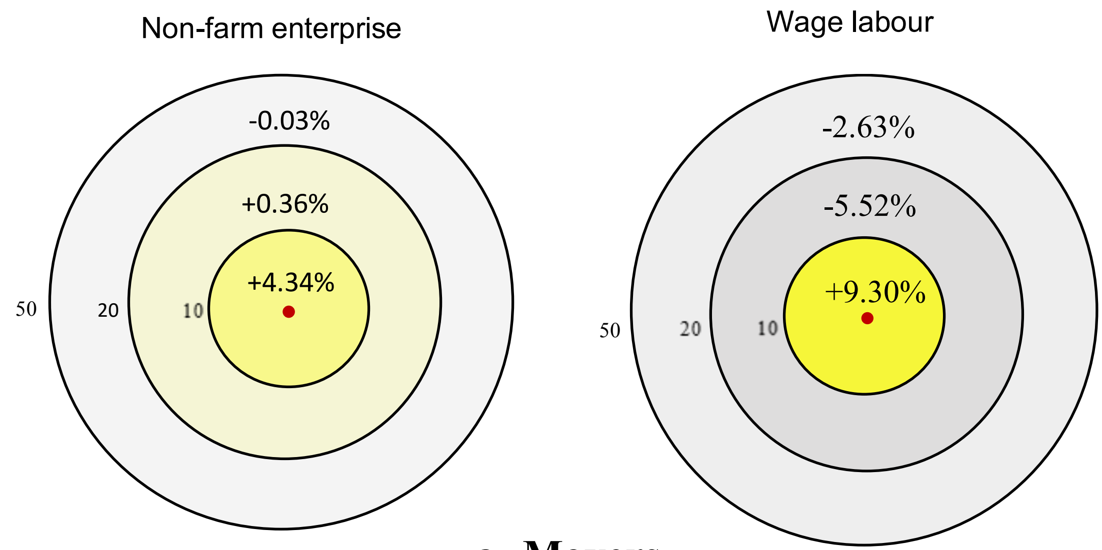
Table 4: Average demeaned urbanisation growth in different concentric circles around different categories of rural workers

	0-10 km around EA*	10-20 km around EA*	20-50 km around EA*	50 km-country border*	N
Employed in non-farm enterprise (Y1-Y2)**					
No-No	**-.0005304**	**-.0098712**	**-.000298**	-2.58e-06	10555
No-Yes	**.0434274**	**.0036803**	**-.0034757**	-.0032515	942
Yes-No	-.0370858	.0287074	.0440364	.0017455	790
Yes-Yes	-.0101034	.1303695	-.0473129	.0029662	603
Employed in wage labour (Y1-Y2)**					
No-No	**-.0032051**	**.001723**	**-.0015904**	.0001446	11534
No-Yes	**.0930292**	**-.0552352**	**-.0263264**	-.0043161	363
Yes-No	-.0140562	-.0079301	.0034593	-.001394	405
Yes-Yes	.052105	-.0053796	.0611685	-.0002787	460
Employed in agriculture (Y1-Y2)**					
No-No	.0270427	-.0775466	.0196506	.0099442	1990
No-Yes	-.0287958	-.0549578	-.0046742	.0069742	1747
Yes-No	-.0168436	.0231068	-.0171385	-.0022641	1006
Yes-Yes	.0016394	.027943	-.0017009	-.0036354	8147
Average change	0.1433	0.1629	0.1529	0.0913	

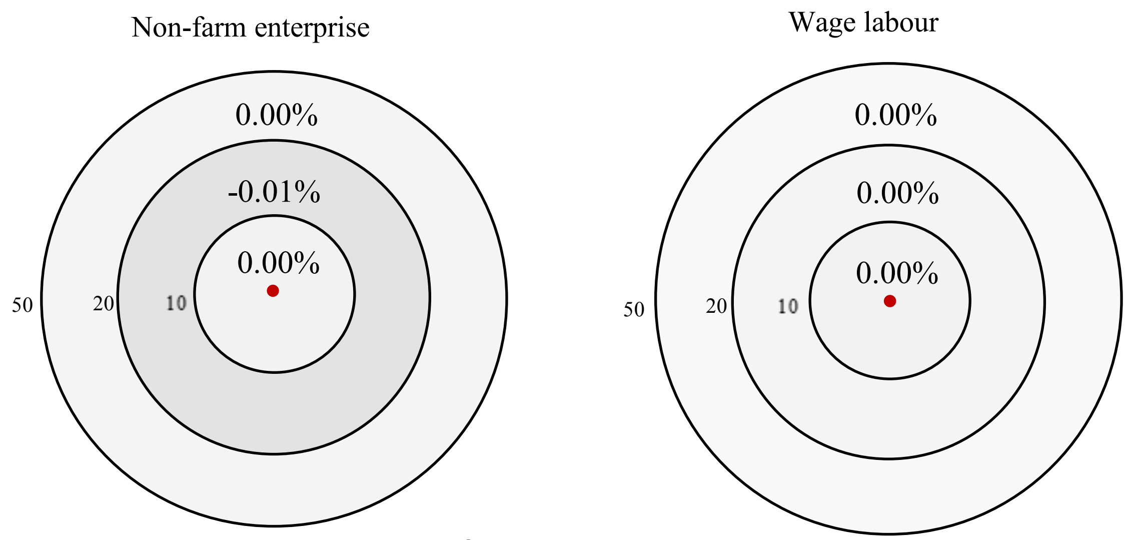
*The urbanisation is measured as the log of SOL formula, demeaned: $\Delta lnSOL_{i0,10} - \overline{lnSOL_{0,10}}$ to facilitate interpretation.

**These variables look at the extensive margin (working in a non-farm enterprise/wage labour/agriculture or not), but individuals are not necessarily working exclusively in these categories. The percentages in bold are illustrated in Figure 3.

***Figure 3**:* Differential urbanisation growth experienced by an average person moving into non-farm enterprise labour or wage labour respectively (a.) versus an average person that did not move into non-farm enterprise labour or wage labour (b).



a. Movers



b. Non-Movers

The top part of this figure (a.) shows what happens in terms of urban growth around an average individual that either moved into working in a non-farm enterprise or into performing wage labour over the period of analysis. The percentage in each concentric circle (or doughnut) indicates the change in urbanisation, trend demeaned. It shows that in both cases over the period between this move, both those who selected into non-farm enterprise labour as well as wage labour, experienced an above average increase of urbanisation (as measured by the sum of lights) in a radius of 10 kilometres around their place of residence, of respectively 4.34 and 9.30 percent. However, in the area further than 10 kilometres from the individuals place of residence, these individuals experienced almost no more than average change in urbanisation in the case of the non-farm enterprise mover, or even below average urbanisation growth in the case of the wage labour mover.

The bottom part of this figure (b.) shows what happens in terms of urban growth around an average individual that did not move into working in a non-farm enterprise or into performing wage labour over the period of analysis. It is clear that these individuals experienced a distinct pattern of urban growth compared with the movers: no above average or even slightly below average urban growth was found in a distance of up to 50 kilometres around their place of residence.

4.0 THE ESTIMATION STRATEGY

As we are interested in the within individual effect over time of urbanisation on rural labour supply, our baseline specification is the following:

$$\boldsymbol{\Delta L_{it} = \beta_1 \Delta u_{it} + \beta_n \Delta c_{nit} + \beta_m c_{i1} + \Delta \varepsilon_{it}} \qquad \textbf{(3)}$$

With $\boldsymbol{\Delta L_{it}}$ the change in labour supply, $\boldsymbol{\Delta u_{it}}$ a measure of change in urbanisation, in our case specified by the SOL or UA constructed variable, $\boldsymbol{\Delta c_{nit}}$ a measure of change in control variable(s), $\boldsymbol{c_{i1}}$ baseline individual characteristics and $\boldsymbol{\varepsilon_{it}}$ a time variant error term. By performing a within transformation on the panel data, we are able to control for all time-invariant unobserved individual characteristics. This is a powerful specification as it assures that our result are not driven by unobserved individual heterogeneity. One of the most important unobserved characteristics that can influence labour supply is undoubtedly ability (Miguel & Hamory, 2009).

4.1 Dependent Variable L

We want to investigate the effect of urbanisation on labour supply in three distinct sectors: non-farm enterprises, wage labour and agricultural labour. By investigating the individual labour supply in each of this sector on the individual level, we avoid assigning individuals to one main sector of employment, as is often done in macro-economic research on labour productivity. In this way, we are able to get a deeper insight on the extent to which individuals on the one hand seek income diversification and secondly seek fuller employment by increasing total working hours.

4.2 Control Variables

We control for both time varying variables and time invariant characteristics by including the baseline characteristics. As time varying control variables, we include eight household size categories: 0-5 years old, 6-14 years old, 15-65 years old and older than 65, each category for both sexes. As baseline characteristics, we include age and gender. This allows us to assess the differential impact of urbanisation on men and women, and on young versus older people.

5.0 RESULTS

Table 5 and 6 investigate the effect of urbanisation growth on labour in the three sectors of interest: non-farm enterprises, wage labour and agricultural labour. It finds that labour supply in all three categories respond positively to an increase in urbanisation.

Table 5 performs an LPM regression of Urban Access as defined by (2) on both non-farm employment and wage employment. The dependent variable indicates whether or not the individual had any non-farm enterprise in the household (column 1 and 2), or performed any wage labour, respectively (column 3 and 4). The results show that an increase of Urban Access with 1 unit, increases the probability of having a non-farm enterprise as well as performing wage labour with 1%.

Table 6 investigates the effect of urbanisation growth on the change in hours worked in the last week preceding the interview. Column (1) and (2) looks at the difference on hours worked in agriculture, while column (3) and (4) look at the difference in hours worked outside of agriculture. It is shown that both measures respond positively to urbanisation: an increase in Urban Access of 1 unit, increases the hours worked in agriculture by approximately 20 minutes and by approximately 30 minutes outside of agriculture.

Although overall effects are reasonably small, they are still significant and show that urbanisation does not lead to a substitution from agricultural labour to non-agricultural labour (such as wage labour or non-farm enterprise labour), but rather leads to an increase in overall hours worked.

Individual are more likely to participate in the labour wage market if its rural area experienced an increase in urbanisation. Similarly, are households more likely to set up a non-farm enterprise when urbanisation increased in the area. This however does not come at the expense of hours worked in agriculture: these also rise in rural areas that are experiencing increasing urbanisation. This suggests that rural individuals and households experiencing urbanisation are more likely to complement their agricultural labour supply with nonfarm employment, while likely also increasing agricultural output due to increasing demand from nearby agglomerations.

This analysis shows that especially nearby urbanisation has profound effects on rural labour supply and has the potential to increase rural labour productivity. Further exploitation of the data will provide a more in-depth analysis on the sectoral and demographic differences of this urbanisation effect, as well as on more precise measures of labour productivity.

Table 5: LPM regression of change in urbanisation on having a non-farm enterprise and being employed in wage labour

	(1)	(2)	(3)	(4)
	∆Non-farm employment	∆Non-farm employment	∆Wage labour	∆Wage labour
∆Urban Access	0.0133***	0.0289	0.0107***	0.0197**
	(0.00347)	(0.0176)	(0.00217)	(0.00993)
∆Urban Access*age		-0.000438		-0.000464
		(0.000824)		(0.000464)
∆Urban Access*age²		1.17e-06		1.50e-06
		(8.70e-06)		(4.77e-06)
∆Urban Access*sex		-0.00455		0.0101**
		(0.00699)		(0.00443)
Age	0.00191**	0.00214**	-0.00131***	-0.00105*
	(0.000973)	(0.00108)	(0.000492)	(0.000551)
Age²	-2.73e-05**	-2.76e-05**	1.07e-05**	1.01e-05*
	(1.11e-05)	(1.22e-05)	(5.32e-06)	(5.97e-06)
Sex	0.00676	0.00922	-0.0116**	-0.0177***
	(0.00701)	(0.00782)	(0.00451)	(0.00495)
Hhsize (8 categories)	Yes	Yes	Yes	Yes
Constant	0.0273	0.0187	0.0244**	0.0192*
	(0.0195)	(0.0216)	(0.0102)	(0.0114)
Observations	12,847	12,847	12,762	12,762
R-squared	0.006	0.006	0.004	0.006

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
The discount factor of urban access is set to α=-2

Table 6: Fixed effects estimation of change in urbanisation on hours worked last week, in agriculture and outside of agriculture

	(1)	(2)	(3)	(4)
	∆H worked last week in agriculture	∆H worked last week in agriculture	∆H worked last week outside of agriculture	∆H worked last week outside of agriculture
∆Urban Access	0.295**	-0.160	0.505***	0.720
	(0.148)	(0.799)	(0.136)	(0.571)
∆Urban Access*age		0.00855		0.00927
		(0.0385)		(0.0273)
∆Urban Access*age²		8.04e-05		-0.000159
		(0.000405)		(0.000289)
∆Urban Access*sex		0.0826		-0.627**
		(0.300)		(0.273)
Age	-0.0738*	-0.0772	-0.105***	-0.112***
	(0.0428)	(0.0501)	(0.0316)	(0.0367)
Age²	0.000373	0.000304	0.00117***	0.00128***
	(0.000475)	(0.000560)	(0.000348)	(0.000402)
Sex	-0.591*	-0.630	2.106***	2.473***
	(0.339)	(0.387)	(0.263)	(0.314)
Hhsize (8 categories)	Yes	Yes	Yes	Yes
Constant	1.136	1.371	-1.925***	-2.013***
	(0.853)	(0.988)	(0.636)	(0.738)
Observations	12,677	12,677	12,642	12,642
R-squared	0.003	0.003	0.010	0.011

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
The discount factor of urban access is set to α=-2

6.0 ROBUSTNESS CHECKS

In this section we will show that our findings are robust to alternative specifications. First of all, do we show that our results our robust to testing for spatial autocorrelation (Moran's I). Further do we investigate the sensitivity of our results to changes in nightlight thresholds as well as different discount factors in the urban access variable. Lastly do we check other robustness checks such as changing the adulthood threshold to 25 years old (McMillan & Harttgen, 2014).

7.0 CONCLUSION

While doubts on the classical economic theory of structural transformation as the major force for economic development have already been made salient, this paper provides evidence that urbanisation can provide opportunities for rural income diversification and thus rural productivity increase. It confirms the premise of McCullough (2017) that labour reallocations are driven by seeking fuller employment, and not necessarily by increasing individual productivity.

McCullough (2017) showed that agricultural labourers have an excess of labour hours to be absorbed by a demand inside and/or outside of agriculture. This paper provides evidence that urbanisation might provide both: demand for agricultural products from surrounding urban centres is stimulating labour inside of agriculture, while the urban economy also provide opportunities to fill employment gaps with hours supplied to non-agricultural sectors (Calì & Menon, 2013). The positive effects on household income might as a consequence stimulate investment in agriculture, which provides another channel for economic growth for the economy as a whole. This is also in line with papers that find evidence for strong growth linkages between the agricultural and non-agricultural sector, as well as the finding from Calì and Menon (2013) that urbanisation has a poverty reducing effect largely due to spill overs from the urban economy, and not necessarily due to rural-urban migration.

Further did this paper find evidence that it is especially nearby urbanisation that is affecting rural labour supply choices. This adds to the continuously expanding literature that shows that growth in small towns can provide an important alley into rural poverty reduction (Christiaensen, 2013; Christiaensen et al., 2017; Christiaensen & Kanbur, 2017; Gibson et al., 2017).

A further understanding of the tight connection between urbanisation and labour patterns is essential for designing policies that may stimulate both agricultural and off-farm economic activities. Until now, rural entrepreneurship has been largely neglected in policy strategies for rural development (Nagler & Naudé, 2013). As Africa's poor still mainly live in rural areas, understanding the livelihood strategies of the rural population is key for informing policies that can strengthen the possibilities of the rural population for fuller employment, and thus initiate rural poverty reduction.

APPENDIX

Table A: Non-farm enterprises survey questions

Ethiopia	Malawi
Over the past 12 months, has anyone in this household ..	Over the past 12 months has anyone in your household…
1) … owned a non-agricultural business or provided a non-agricultural service from home or a household-owned shop, as a carwash owner, metal worker, mechanic, carpenter, tailor, barber, etc.?	1) … owned a non-agricultural business or provided a non-agricultural service from home or a household-owned shop, as a carwash owner, metal worker, mechanic, carpenter, tailor, barber, etc.?
2) … processed and sold any agricultural by-products, including flour, local beer (tella), 'areke", "enjera", seed, etc., but excluding livestock by-products, fresh/processed fish?	2) … processed and sold any agricultural by-products, including flour, starch, juice, beer, jam, oil, seed, bran, etc., but excluding livestock by-products, fresh/processed fish?
3) … owned a trading business on a street or in a market?	3) … owned a trading business on a street or in a market?
4) … offered any service or sold anything on a street or in a market, including firewood, home-made charcoal, construction timber, woodpoles, traditional medicine, mats, bricks, cane furniture, weave baskets, thatch grass etc.?	4) … offered any service or sold anything on a street or in a market, including firewood, home-made charcoal, curios, construction timber, woodpoles, traditional medicine, mats, bricks, cane furniture, weave baskets, thatch grass etc.?
5) … owned a professional office or offered professional services from home as a doctor, accountant, lawyer, translator, private tutor, midwife, mason, etc?	5) … owned a professional office or offered professional services from home as a doctor, accountant, lawyer, translator, private tutor, midwife, mason, etc?
6) … driven a household-owned taxi or pick-up truck to provide transportation or moving services?	6) … driven a household-owned taxi or pick-up truck to provide transportation or moving services?
7) … owned a bar or restaurant?	7) … owned a bar or restaurant?
8) … owned any other non-agricultural business, even if it is a small business run from home or on a street?	8) …owned any other non-agricultural business, even if it is a small business run from home or on a street?

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