Can Urbanization Improve Household Welfare? Evidence from Ethiopia

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Abstract:

Despite evolving pieces of evidence showing that Africa is urbanizing differently, empirical evaluations on the welfare implications of urban development programs in Africa remains scant. In this paper, we employ satellite-based night light intensity data to capture urban growth and explore the implication of urbanization on households' welfare. We merge household-level longitudinal data with satellite-based night light intensity and investigate the welfare implication of recent urbanization trends in Ethiopia. We find that urban growth, mainly expansion of small rural towns, as measured by night light intensity, is associated with significant welfare improvement. This pattern holds for both ultimate measures of welfare as well as intermediate labor market outcomes of households. We particularly find that one unit (Digital number) increase in night light intensity is associated with about 2 percent improvement in household welfare. Similarly, urban growth improves households' engagement in non-farm economic activities. However, we also find suggestive evidence insinuating that potential dynamics in urban expansion may slightly trigger welfare inequality among households living in a specific community while also increasing the real price of food items. Nevertheless, the size of effects on welfare inequality and price of food items are marginal, implying that the positive welfare implications of urban expansion may outweigh. Our results have important implications in terms of informing public policy debates on the consequences and implication of urban expansion in Africa.

Keyword: urban growth, night light intensity, welfare, labor market outcomes.

1. Introduction

The world has experienced unprecedented levels of urbanization with highest urban growth rates coming from developing countries. Africa is expected to be the fastest urbanizing continent from 2020 to 2050 (United Nations, 2014). In particular, many argue that Africa's urbanization trends remain distinct (Jedwab, 2012; Henderson et al., 2013) and Africa is urbanizing without growth (Fay and Opal, 2000) and without industrialization (Gollin et al., 2016). The paces of urbanization in many African countries are surpassing the required levels of structural and political transformations to accommodate this rapid urban expansion, and hence leading to proliferation of slums and informal sectors.[1]

These rapid urbanization trends are presenting new opportunities and challenges for ensuring sustainable and inclusive growth. Indeed, urban poverty and youth unemployment are the major challenges facing urban centers in sub-Saharan Africa countries (African Development Bank, 2011). Recent studies indicate that poverty has been urbanizing (Ravallion et al., 2007) and hence becoming urban phenomenon (Dorosh and Thurlow, 2014); economic inequality has been growing in African urban centers (World Bank, 2013). Urbanization of poverty is mainly argued to be driven by migration of the rural poor to urban areas, often associated with unplanned urbanization (Ravallion et al., 2007; Elhadrary and Samat, 2012). Urban residents are believed to be vulnerable to climate shocks (Cohen and Garrett, 2010) and price shocks (Alem and Söderbom, 2012).[2]

On the other hand, some other empirical studies highlight positive effects and implications of urban expansion. Urbanization involves shifting of employment opportunities from agriculture to more remunerative industrial and non-farm employment opportunities (Bloom et al., 2008; Henderson, 2010; Diao et al., 2019). Other recent studies show that urbanization improves market linkages by increasing demand for high-value agricultural products and non-farm employments (Cali and Menon, 2012; Datt et al., 2016; Siwan and Teufel, 2017; Youssef et al., 2016; Vandercasteelen et al., 2018). Urbanization improves access to markets and hence may generate higher income to support rural livelihoods (Cali and Menon, 2012). Urbanization involves

[1]This is reflected by the fact that 62% of urban residents in Africa are living in slums with high and rising rates of youth unemployment (World Bank, 2013).
[2]When the world's urban population surpassed rural population for the first time in 2008, poor African urban dwellers were disproportionally hit by the 2008 food price rise (Cohen and Garrett, 2010).

movement of people from remote and rural areas to urban areas, a trend that may affect labor market outcomes of urban and rural dwellers (e.g., Henderson et al., 2017).

Despite evolving pieces of evidence showing that Africa is urbanizing differently, empirical evaluations on the welfare implications of urban development programs in Africa are missing. In particular, the implications of urbanization trends in sub-Saharan Africa on household welfare outcomes are not well-explored. The scarcity of empirical studies on the implication of urbanization can be partly attributed to lack of an objective measure of the level and dynamics of urbanization. Previous attempts employ coarse aggregate measures and definitions of urbanization, measures which cannot adequately capture potential heterogeneities among urban areas and the rapid dynamics of urbanization (Champion and Hugo, 2004; Dahly and Adair, 2007; Amare et al., 2018). These census-based rural-urban indicators are unable to uncover potentially complex and nonlinear relationships between urbanization and households' livelihood outcomes. Rather than a binary phenomenon, urbanization involves a continuum of rural-to-urban transformation at various stages and pace. Thus, exploring the implication of urbanization on households' welfare and livelihood using alternative and reliable metrics of urbanization is crucial for informing urban development programs in Africa. The advent of satellite-based night light data offers interesting potential to measure urbanization and urban expansion. Given that night light remains one of the fundamental urban amenities, night light intensity is argued to be a plausible marker of urbanization and urban growth (e.g., Elvidge et al., 1997; Imhoff et al., 1997; Sutton, 1997). This is particularly appealing for sub-Saharan African countries where measures and statistican indicators of urbanization are not readily available and standardized. Recent studies have successfully applied the night light intensity data for studying the implication of urbanization in Africa (Michalopoulos and Papaioannou, 2013; Storeygard, 2016; Abay and Amare, 2018; Amare et al., 2018).

In this paper, we employ satellite-based night light intensity data as markers of urban growth to study the implications of urbanization on households' welfare and livelihood in Ethiopia. We are particularly interested in identifying whether recent urbanization trends, mainly expansion of small rural towns, in Ethiopia are improving household welfare and household livelihoods. Urban development programs in Ethiopia share most of the challenges that African urban centers are facing. Despite from a low base, with urban population of about 20 percent, annual urban growth in Ethiopia amounts about 4.5 percent, which is higher than the sub-Saharan African average (World Bank, 2011). Cognizant of this trend, the Ethiopian government is recently giving due policy attention to existing trends in the urbanization process (FDRE, 2016). Indeed, monitoring recent trends in urban expansion has been incorporated in the Growth and Transformation Plan (GTP-II) of the government Ethiopia. Evolving urban growth in Ethiopia provides a unique opportunity to proactively manage and regulate urban development programs to ensure inclusive and sustainable growth. Despite some attempts, the welfare implications of recent trends in urban expansions in Ethiopia remain unexplored. Indeed, some anecdotal pieces of evidence show that recent trends in urban expansion in Ethiopia may not be equally benefiting all groups of societies (e.g., Broussard and Teklesellasie, 2012; Mezgebo, 2017).

We assemble geo-referenced and nationally representative household-level longitudinal data coming from the Living Standard Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) for Ethiopia. The LSMS-ISA household surveys follow similar households across time, providing longitudinal variation in our measure of urban expansion as well as households' welfare and livelihood outcomes. We merge these longitudinal household data with satellite-based time series night light intensity data coming from the US Defense Meteorological Satellite Program Operational Linescan System (DMSP-OLS). We exploit these longitudinal variations in urban expansion (night light intensity) and examine the welfare implication of such dynamics in urbanization. Due to the nature of our sample, which consists of rural and small towns, we focus on expansion of small rural towns and examine the implication of these dynamics on household welfare. We estimate alternative forms of fixed effects models, which exploit longitudinal variations in our measures of urbanization and household welfare.

We find that urban growth, mainly expansion of small rural towns, as measured by night light intensity is associated with household welfare improvement. This pattern holds for both direct measures of welfare, mainly real consumption, as well as intermediate labor market outcomes of households. We particularly find that one unit (Digital number) increase in night light intensity is associated with about 2 percent improvement in household welfare. Similarly, night light intensity is strongly associated with improved labor market outcomes and opportunities. More specifically, expansion of small rural towns improves households' engagement in non-farm economic activities. Our findings relate the literature that identifies effects of small towns expansion on household welfare (Christiaensen et al., 2013; Christiaensen and Kanbur, 2017; Gibson et al., 2017).

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However, we also find suggestive evidence insinuating that potential dynamics in urban expansion may slightly trigger welfare inequality among households living in a specific community while also increasing the real price of food items. Our quintile and inequality regressions suggest that those households in higher consumption quintiles enjoy slightly higher welfare gains from urban growth. Similarly, our food price analysis suggests that urbanization, as measured by night light intensity, is associated with higher real price of food items. Nevertheless, the size of effects on welfare inequality and price of food items are marginal, implying that the aforementioned positive welfare impact of urban expansion may outweigh. Our results have important implications in terms of informing public policy debates on the consequences and implication of urban expansion in Africa.

2. Urbanization and household welfare: A review

There are several important channels through which urbanization can affect household welfare. Urbanization is closely related to higher productivity and structural transformation, leading to higher welfare in the long-term (World Bank, 2009; Gleaser, 2011). This rural-urban transformation is expected to involve shifting of employment opportunities from agriculture to more remunerative industrial, non-farm as well as other types of urban employment opportunities (Bloom et al., 2008; Henderson, 2010). Growth of small and large towns can create non-farm employments and increase income opportunities for the youth (de Brauw and Mueller, 2012). This may also shift the primary source of income and employment of rural households living in proximity to these small and large towns (Diao et al., 2019). Consistent with this channel, recent studies show that urbanization rates are positively associated with higher income per capita (Dorosh and Thurlow, 2014; Henderson, 2010; Ravallion et al., 2007; Bloom et al., 2008) and more diversified income portfolio (Mezgebo and Porter, 2019).

Urbanization may also influence rural households' welfare by enhancing investments on farming technologies and creating market opportunities for agricultural products (Swain and Teufel, 2017). Urban expansion may encourage rural households' tailor their agricultural production patterns in a way that can generate higher monetary returns (Stage et al., 2010; Vandercasteelen et al., 2018) than enable them join middle income category (Diao et al., 2019).

Despite these positive channels, urban expansion may also affect urban households' welfare negatively. Urban growth is often associated with increasing demand for food products and public services. When this increasing demand is coupled with nearly inelastic supply, which is often the case in distorted market systems, increasing demand for food products may also lead to increase in prices. This increase in food prices and associated shocks may affect urban dwellers disproportionally (Alem and Soderbom, 2012).

Urbanization is also theoretically associated with income inequality, particularly at early stages of urbanization (Kuznets, 1955; Kanbur and Zhuang, 2013). This is particularly believed to be the case when investments on infrastructure and institutions are limited, a common pattern in many developing countries experiencing recent urban expansions (Balack and Henderson, 1999). Recent urbanization trends in sub-Saharan Africa (SSA) are not accompanied with adequate investments and hence not resulting in required levels of industrialization (Jedwab, 2012; Henderson et al., 2013). This imply that the bottom poor households may gain little from emerging urbanization and hence the latter can increase income inequality in the short to medium term. These patterns are consistent with the widening consumption gaps in some of the countries experiencing rapid urban expansion. For instance, in the context of Ethiopia, the urban income inequality (with a Gini coefficient of 0.38) is higher than the rural income inequality (with a Gini coefficient of 0.28) (CSA, 2019).

The above short review highlights several important insights. Most importantly, the net welfare effect of urbanization depends on the relative impacts of urbanization on some of the positive and adverse effects. Thus, whether urbanization improves overall household welfare remains far from settled. As a consequence of the multidimensional effects of urban growth, understanding the overall effects of urbanization requires studying the various attributes and implications of urban expansion. For this reason, besides quantifying the overall effects of urbanization, we also explore potential mechanisms and channels through which urbanization can affect household welfare. We particularly investigate the implication of urbanization on some of the above channels, including the impact of urban expansion on households' labor market outcomes as well as real prices of food items. However, it is worth noting that urbanization may involve some other structural transitions that complicate identification of potential channels through which urbanization can affect household welfare and labor market outcomes. Thus, the channels we discuss here and explore in our empirical exercise are not probably sufficiently exhaustive. As we discuss below, our sample consists of rural and small towns, implying that the type of urbanization we are studying may be distinct from the typical urbanization that involves creation of major towns and cities, which may have slightly different implication relative to expansion of small towns (Christiaensen et al., 2013; Christiaensen and Kanbur. 2017; Gibson et al., 2017).

3. Data and Measurement of Key Variables

2.1 Data and descriptive statistics

We use two different data sources, namely the Living Standard Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) for Ethiopia[3] and satellite-based night light intensity data gathered by the US Defense Meteorological Satellite Program Operational Linescan System (DMSP-OLS). The Ethiopian LSMS-ISA data are nationally representative longitudinal datasets collected every two years, covering a wide range of topics related to production and consumption decisions of rural and urban households. More importantly, the LSMS-ISA data provide geo-referenced households and enumeration areas (EA).[4] These features allow us to merge the LSMS-ISA data with the DMSP-OLS night light intensity data using the geo-reference of enumeration areas.

We use two waves of the LSMS-ISA for Ethiopia: the first survey was conducted in 2011/12 while the second wave comes in 2013/14. The first wave, covering only rural areas and small towns, interviewed a sample of households in 333 EAs throughout all regional states of Ethiopia. The second round re-interviewed the 2011/12 sample households, including major towns and cities, increasing the sample to 433 EAs.[5] We employed Version 4 of the DMSP-OLS time series for the night time light data, which covers only 1992 through 2013.[6] For this reason, we are not using the latest and more recent round of the LSMS-ISA data for Ethiopia. We delineated a 10 square kilometres zone around LSMS-ISA enumeration areas and, then, extract mean daily night light intensities as well as maximum night intensities associated with the survey sites. Table 1

[3] The World Bank LSMS-ISA initiative provides financial and technical support to the Central Statistical Agency of Ethiopia in designing and implementing of the survey as well as analysing and disseminating the survey results.
[4] In the context of Ethiopia, an enumeration area covers about 150-200 households in rural areas and 150-200 housing units in urban areas.
[5]The Central Statistics Agency (CSA) defines small town as urban areas with a population less than 10, 000, while large towns are those with a population size of 10,000 and above.
[6] After 2013, a different version known as Version 1 VIIRS night lights series was introduced, which is not directly comparable with DMSP-OLS due to wide differences in spatial resolution.

provides descriptive statistics of household and community level characteristics. We mainly report households' basic demographic and socioeconomic characteristics, those which are expected to influence the consumption and production decisions of households. We disaggregate and present these descriptive figures across the two waves. As the first round covers only rural areas and small towns, our final sample excludes those households from large towns which joined in the second round. This implies that the type of urbanization we are studying here mostly involves expansion of small rural towns, which is slightly different to the usual large-scale creation of large towns and cities. The summary statistics given in Table 1 are plausible. For instance, for the first round, female headed households represent 25 percent of our sample, while this share amounts 26 percent in the second wave. For most variables, the means and standard deviations are comparable across both rounds. The census-based urbanization indicator, urban dummy, remains identical in both rounds, implying that these types of aggregate indicators cannot capture short-term urbanization trends and dynamics. Again, the rural-urban census-based indicator shows that we are studying the implication of slight expansion and growth of small towns in mostly rural areas. However, night light intensities can capture even these small changes in urban growth. Furthermore, as we are focusing on two rounds and hence urban expansion realized in two years' time horizon, any potential impacts of urban expansion are short-term effects.

Table 1: Summary statistics of sample households

	2011 round		2013 round	
	Mean	SD	Mean	SD
Household head characteristics				
Female head	0.25	0.43	0.26	0.44
Age of head	44.01	15.73	45.81	15.32
Household size	4.81	2.37	5.54	2.51
Head attended school (0/1)	1.63	0.48	1.64	0.48
Average age of household	27.29	12.02	24.55	12.12
Household wealth indicators				
Farm size (ha)	0.89	1.69	1.17	3.4
Corrugate iron sheet	0.42	0.49	0.48	0.49
Livestock (TLU)	3.43	5.54	3.97	5.2
Distance and access				
Urban dummy (0/1)	0.12	0.33	0.12	0.33
Access to microfinance	0.29	0.45	0.29	0.45
Access to formal credit	0.08	0.27	0.09	0.29
Distance to nearest major road	16.26	19.05	16.17	18.9

Distance to nearest market	68.06	48.65	67.84	49.05
No. observations	3611		3513	

2.2 Defining and describing welfare and related outcomes

We use real consumption expenditures as a proxy for households' welfare. We adjusted the consumption expenditures to 2011 prices using the consumer prices indexes (CPI) of the Central Statistics Agency (CSA) of Ethiopia. The consumption expenditures include both home produced and purchased food items consumed by the household.[7] We employ both temporal and spatial price indexes to convert nominal consumption to real consumption. We particularly employ temporal consumer price indexes provided by the CSA of Ethiopia.[8] To account for the household's age and sex composition, the consumption expenditures are in adult scales using the indexes available in LSMS-ISA dataset. Table 2 provides summary statistics associated with our welfare indicators. We disaggregate and present these figures across alternative indicators of urbanization coming from census-based indicators. That is, we provide summary statistics for rural areas and small towns. Real consumption expenditures of households have decreased over years, both for rural and urban households. This is consistent with some other recent studies investigating the welfare dynamics of Ethiopian households using similar data (e.g., Fuje, 2018). As expected, consumption remains higher for those households living in small towns, compared to those living in rural areas. Those household in small towns and urban areas spend relatively larger share of their income on non-food items. This is not surprising given that households in small towns and urban centres have better access to services such as power, communication, schools and other sanitation services. This potentially creates difference in terms of spending on the items which ultimately lower level of expenditure in rural areas.

The lower panel of Table 2 provides summary statistics associated with labor market outcomes and labor allocation of households, one potential channel through which urbanization may improve household welfare. The values of these indicators are reasonably comparable across both rounds, partly attributable to the similar timing of data collection across both rounds. As

[7] Local prices are applied to value consumption of home-produced foods.
[8] We also employ the spatial regional price indexes given in the LSMS-ISA data to account for spatial variations in prices and inflation rates.

expected, most farming activities are prevalent in rural areas while non-farm activities are most practiced in small towns and urban areas.

Table 2: Summary of consumption and related welfare indicators

	2011		2013	
	Rural	Small towns	Rural	Small town
Consumption and other indicators	Mean	Mean	Mean	Mean
Real annual consumption per adult equivalent (ETB)	5331.3	7242.4	4325.4	6329.1
Food consumption per adult equivalent (ETB)	4373.8	4815.2	3460.6	4189.1
Non-food consumption (ETB)	856.8	2082.9	834.7	1774.3
Labor supply and labor market indicators				
Total hours worked over the last 7 days (per adult)	18.6	22.4	14.9	18.0
Hours worked on farm activities (per adult)	13.0	2.8	12.6	3.4
Hours worked on non-farm activities (per adult)	5.6	19.6	2.3	14.6
No. Observations	3,103	471	2,948	436

Notes: Consumption values are deflated using temporal and spatial price index deflators. Consumption values are expressed in 2011 and reported in Ethiopian birr (ETB). Labor supply and labor market outcomes of households are measured in hours worked over the last 7 days and computed per adult household members.

2.3 Defining and measuring urbanization and urban growth

Despite the unprecedented levels of contemporary rural-to-urban transformations in developing countries, researchers and urban planners are still exploring for more accurate measures of the level and dynamics of urbanization. Most measures of urban expansions, which are usually binary rural-urban indicators, come from population censuses and hence inadequate to sufficiently capture the rapid dynamics in urban expansion. Most of these indicators are aggregated at higher levels, inhibiting micro level analysis of the impact of urbanization on households' livelihood. As most census-based indicators are constructed every 10 years, this measurement problem is not unique to developing countries.[9]

These measurement challenges have encouraged researchers and urban planners to actively look for alternative measures or markers of urbanization. More recently, efforts have focused on constructing continuous and disaggregate indicators that can capture micro-level variations in urban expansion. For this purpose, the satellite-based night light intensity data has

[9] Even those census-based rural-urban indicators in the United States and Europe may be insufficient to inform the dynamics of urbanization (Imhoff et al., 1997).

attracted a lot of attention and potential to reasonably capture the dynamics of urbanization and related economic activities. As access to electricity and lights remain key urban amenities, urban areas are expected to have higher night light intensity than rural areas. Based on this notion, satellite-based night light intensity has been commonly used as a marker of urbanization (Elvidge et al., 1997; Imhoff et al., 1997; Henderson et al., 2003; Sutton et al., 2010; Storeygard, 2016; Amare et al., 2018; Abay and Amare, 2018).

Following this trend, we measure urbanization and urban growth by using night light intensity coming from remote sensing data. The satellite-based luminosity data come from the Defense Meteorological Satellite Program Operational Linescan System (DMSP-OLS) of the United States Air Force. The DMSP-OLS collects daily light intensity data from every location on the planet at about a one square-kilometre resolution. These data are further processed by the National Geophysical Data Centre (NGDC) of the United States' National Oceanic and Atmospheric Administration (NOAA) processes. The luminosity data measures and expresses light intensity in digital numbers (DNs) ranging from 0 (no light) to 63 (highest light) for each square-kilometre pixel.[10] We employed Version 4 of the DMSP-OLS time series, which covers only 1992 through 2013. A 10 km zone was delineated around LSMS-ISA enumeration areas and we extract mean night light intensities as well as maximum night intensities associated with these locations. After 2013, another version of the luminosity data, Version 1 VIIRS Night Lights series, was introduced. However, DMSP-OLS (1992-2013) and VIIRS night lights are not directly comparable due to wide differences in spatial resolution.

The luminosity data have novel features that are helpful for mapping urban growth. Most importantly, the longitudinal nature of these data and the availability of these data at high spatial resolution allow us to trace the dynamics of urbanization at micro-level. In spite of the increasing use night light intensity to approximate the levels and dynamics of urbanization, these data suffer from some limitations (see, Donaldson and Storeygard, 2016; Michalopoulos and Papaioannou, 2018). First, although less relevant to our context, night light data are censored at higher level of the distribution, implying that these data may understate the level of light intensities for a small fraction of areas with high levels of lighting (urbanization). Second, night light intensity data do not differentiate luminosity caused by human activities and those caused by artificial lights for

[10] These values can be further averaged for every geographic area of interest (e.g., village, district, state, or country).

example those caused by gas production (Elvidge et al., 2009).[11] Considering our context, the luminosity data are highly skewed to the left, mainly because many parts of the developing world are dark (Michalopoulos and Papaioannou, 2018). This is the case in our context because our household level data covers large part of rural Ethiopia. However, as we show in our estimations, these skewed luminosity data provide more variation and dynamics than the commonly used rural-urban indicator.

We merged the longitudinal LSMS-ISA data for Ethiopia with the satellite-based night light intensity data from the DMSP-OLS.[12] Table 3 provides the dynamics of these indicators of urbanization. Despite from a low base, average, maximum and total night light intensity increased over the two years period from 2011 to 2013. For instance, the average night light intensity increased by about 20 percent. Figure 1 provides the distribution of the night light intensity across both waves. This figure shows that the share of low night light intensity decreases while the share of high intensity categories increases across waves. For instance, the share enumeration areas with zero DN night light in 2011 was 69 while this shrunk to 59 in 2013. This is not surprising given the recent infrastructural investments by the Ethiopian government. We aim to explore whether these dynamics in these indicators of urbanization can predict and cause potential welfare improvements.

Table 3: Summary statistics of key explanatory variables

	2011		2013	
Indicators of urbanization	Mean	Standard deviation	Mean	Standard deviation
Mean night light intensity (DN)	0.31	1.24	0.38	2.03
Maximum night light intensity (DN)	3.25	7.45	3.38	8.52
Total (sum) of nightlight intensity (DN)	80.71	357.97	104.13	663.12

Notes: Night light intensity is measured using digital numbers (DN).

[11] Third, the luminosity data do not distinguish differences in light intensity caused by variations in infrastructures (e.g., factories and transportation hubs) or natural actions, implying that the data may not accurately capture levels of urbanization in areas where artificial lights and gas flaring may be common (see, Elvidge et al., 2009).

[12] These datasets can also help us explore some country-specific and unique features of urban expansion in Ethiopia and its implications.

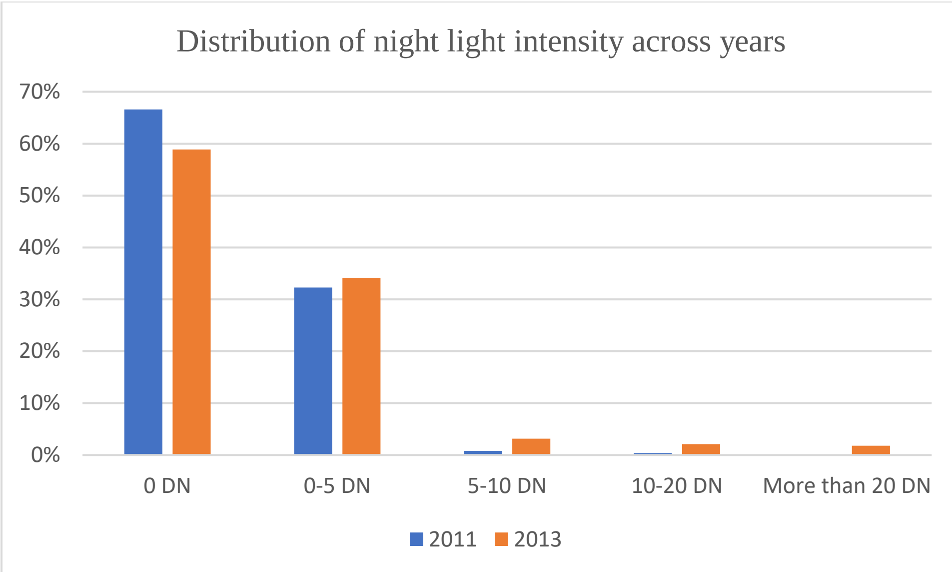

Figure 1: Distribution of night light intensity across years.

4. Identifying the Impact of urbanization on welfare: Empirical Strategy

4.1 Econometric Specifications

Quantifying the impact of urbanization involves several empirical challenges, including endogeneity problems arising from omitted attributes and measurement problems. This is not surprising given that most urbanization programs are accompanied by economic growth that can influence the overall livelihood of societies. In view of these empirical challenges and features, we employ alternative econometric approaches that exploit the cross-sectional and longitudinal variations in our measure of urbanization. As we employ two waves of the LSMS-ISA data, we will be following the same households across waves as well as urbanization trends of enumeration areas. Thus, we particularly exploit the implication of potential temporal variations in our measure of urbanization.

As we conduct our analysis at the household-level, potential dynamics in urbanization can be exogenous to short-term livelihood outcomes. Hence, we exploit the longitudinal variations in our measure of urbanization by estimating household fixed effects models. These fixed effect models are immune to time-invariant differences across villages and households. This is a relatively conservative approach as it requires reasonable variations in our measure of urbanization across time.

We employ consumption values, specifically real consumption per adult equivalent, as our direct measure of welfare. Thus, our estimable welfare function is specified below:

$$\ln C_{hvt} = \beta_1 U_{vt} + \beta_2 H_{hvt} + \delta_h + \delta_t + \varepsilon_{hvt} \quad (1)$$

Where $\ln C_{hvt}$ stands for logarithmic values of real consumption per adult equivalent for household *h* residing in an enumeration area (EA) *v* for period *t*. U_{vt} stands for the level of urbanization for each enumeration area (village) and time, while H_{hvt} capture additional household and village characteristics. δ_h and δ_t represent household and time fixed effects, respectively. The specification in equation (1) is immune to time-invariant household and village-level heterogeneities. Hence, in the absence of time-varying unobservable factors which affect both consumption and urbanization, β_1 identifies the effect of urban growth on household welfare.

Besides quantifying the overall impact of urbanization on household welfare, we also explore potential mechanisms as well as additional effects of urbanization on welfare distribution. As one important channel through which urbanization can improve household welfare, we particularly estimate the implication of night light intensity on households' labor market outcomes. We estimate similar regressions for identifying potential mechanisms as well as for quantifying the impact of urbanization on welfare distribution (economic inequality) among households living in the same enumeration area.[13]

Given that households have little influence on urban expansion, we can argue that the empirical specification in equation (1) can reasonably identify the impact of urban growth on household welfare. To circumvent endogenous dynamic migration decisions, we control for additional controls including family size at each time as well as other time-varying controls. However, one may still imagine that some dynamic shocks and government interventions can simultaneously affect urban development programs and the welfare of households. To minimize such contemporaneous shocks to our outcomes and the explanatory variables, we control for additional community level attributes. We also consider alternative construction of our measure of urbanization. We compute average, maximum and total night light intensity in a specific enumeration area. Our key variables of interest vary at village (enumeration area) level, implying

[13] Thus, we aim to conduct village-level analysis of economic inequality and estimate equation (1) at enumeration area (village) level.

that households living in the same village can share some unobserved effects. Thus, in all our estimations, we cluster standard errors at village level.

5. Estimation Results

Before presenting our main results, the following clarifications are in order. Our outcome variable is expressed as logarithmic transformation of real consumption per adult equivalence. Our proxy for urbanization is night light intensity. We construct average, maximum as well as total night light associated with a specific enumeration area. Night light intensity is measured and expressed in digital numbers (DNs), which ranges from 0 (no light) to 63 (highest light) for each enumeration area.

Table 4 provides estimates based on average night light intensity associated with specific enumeration area. The first column exploits cross-sectional variation in night light intensity. The second and third columns control for enumeration area and household level fixed effects, respectively. The enumeration area fixed effects can capture time-invariant community level heterogeneities across space. Similarly, the household fixed effects control for time-invariant household-level heterogeneities among households. Thus, we are exploiting longitudinal variations in urbanization to identify the impact of urban growth on welfare growth. Our outcome variable is adjusted for temporal and spatial variations in inflation, and given in per adult equivalence. We can clearly observe that higher night light intensity (urban growth) is associated with higher consumption per adult equivalence. More specifically, a 1 DN increase in night light intensity is associated with about 2 percent increase in household consumption. The effects remain robust even after controlling for important time-varying covariates. Given the low level of light intensity in our sample, the size of the effect is plausible. These impacts are particularly considerable given the overall downward trend in household welfare observed in our data and other Ethiopian studies employing similar datasets (e.g., Fuje, 2018).

In Table A1 (in the appendix) we provide slightly different estimates based on maximum and total night light intensity associated with specific enumeration areas. We follow similar specifications as in Table 4 and hence all estimates control for some form of fixed effects, enumeration area or household-level. The first two columns are based on maximum night light intensity while the last two columns employ total (sum) night light intensity associated with a specific enumeration area (the delineated 10 km buffer zone). These results confirm those in Table

4, implying that the maximum or total night light intensity around a specific location is associated with higher household welfare.

Besides highlighting the welfare implication of urbanization, the results in Table 4 and A1 reinforce the potential of night light intensity to detect short-term urban growth and associated trends. This is unlike the conventional census-based urbanization indicators. In all our estimations we include census-based measures of urbanization using an indicator variable for urban areas. Despite capturing significant spatial variations in consumption among households (as shown in column 1 of Table 4), this indicator shows little (no) temporal dynamics and hence vanishes in our fixed effects estimations. This implies that our measure of urbanization, night light intensity is capturing short-term effects of urbanization and associated trends, which otherwise cannot be captured by conventional census-based indicators of urbanization. This is particularly encouraging from a measurement point of view.

The signs and relationships between the other variables of interest and household welfare are consistent with our expectations and previous evidence. Focusing on the fixed effects estimates in column 3 of Table 4, larger household size is associated with lower welfare. However, the composition of household members seems to matter. Increasing average age of household members is associated with higher welfare. This is not surprising as increase in average age of household members imply more working hands that can generate more income to the household. As expected, asset ownership predicts higher welfare as shown by the positive association between livestock ownership and household welfare. Those households with non-farm income have higher welfare.

To uncover potential heterogeneities in the impact of night light intensity (urbanization) on household welfare, we also estimate quantile regression specifications. Figure 2 provides the effects of night light intensity across the welfare percentiles. These estimates suggest a slightly increasing trend and effect associated with night light intensity. For instance, the impact of urbanization at the last two welfare percentiles are slightly higher than those at first two welfare percentiles. Those households in the lower and higher welfare percentiles are more likely to benefit from urban expansion while the effect for those in the middle percentiles seem statistically insignificant. This finding is consistent with the evidence from Chile and Colombia (Berdegue et al, 2015). Overall, these results have important implications in terms of highlighting the heterogenous impacts of urban expansion. To uncover further heterogeneities and implications of urban expansion, we further prob this question in Section 6.2.

Table 4: Night light Intensity and household welfare

Explanatory Variables	(1) Log (real consumption)	(2) Log (real consumption)	(3) Log (real consumption)
NTL (mean)	0.016***	0.016***	0.019***
	(0.005)	(0.003)	(0.003)
Gender of household head	0.015	0.022	-0.023
	(0.026)	(0.021)	(0.096)
Ln (age of household head)	-0.211***	-0.255***	-0.093
	(0.043)	(0.036)	(0.144)
Education head (dummy)	0.192***	0.128***	-0.014
	(0.025)	(0.020)	(0.038)
Household size	-0.061***	-0.062***	-0.054***
	(0.006)	(0.004)	(0.017)
Ln (average age in household)	0.237***	0.248***	0.329***
	(0.036)	(0.035)	(0.058)
Farm size (ha)	0.001	0.003**	0.001
	(0.001)	(0.001)	(0.001)
Urban (dummy)	0.245***	0.000	0.000
	(0.052)	(0.000)	(0.000)
Ln (TLU)	0.083***	0.112***	0.058***
	(0.015)	(0.013)	(0.021)
Non-farm income (dummy)	0.033	0.003	0.058*
	(0.026)	(0.021)	(0.035)
Access to micro finance	0.058	0.053	0.049
	(0.042)	(0.057)	(0.057)
Access to formal credit	-0.039	-0.005	-0.070
(borrowed from formal source)	(0.032)	(0.028)	(0.042)
Enumeration area FE	No	Yes	Yes
HH fixed effects	No	No	Yes
Year dummies	Yes	Yes	Yes
R-squared	0.19	0.41	0.73
No. observations	6478	6478	6478

Notes: NTL stands for night light intensity. In this table we are employing mean night light intensity across a buffer zone of 10 kilometres square. Standard errors, clustered at enumeration area level, are given in parenthesis. $^{*}p< 0.10$, $^{**}p< 0.05$, $^{***}p< 0.01$.

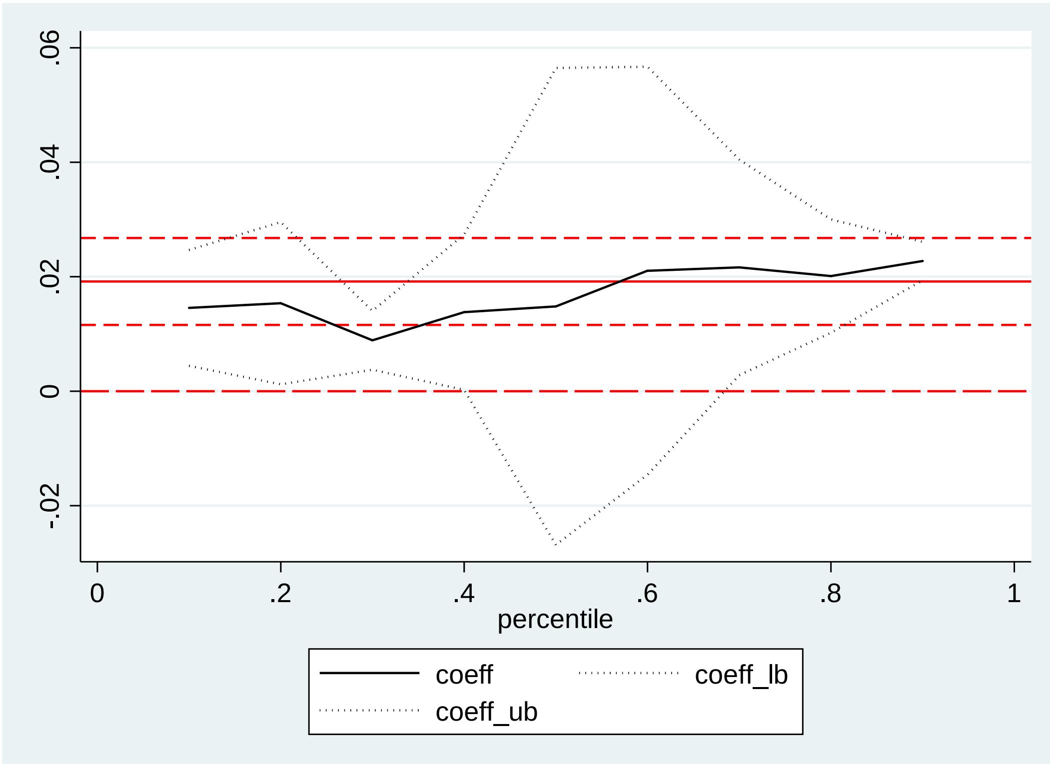

Figure 2: Quantile regressions results on the impact of night light intensity.

6. Potential mechanisms and additional effects

6.1. Urbanization and households' labor market outcomes

Following the discussion on potential channels and mechanisms through which urbanization can affect household welfare, we explore and test some of the usually proposed channels. One of the key channels identified in the literature is related to the impact of urbanization on labor productivity and hence households' labor market outcomes. Following this hypothesis, we explore the impact of night light intensity on labor market outcomes of households. The Ethiopian LSMS-ISA data provide information on time use and labor allocation outcomes for all household members and for the last 7 days. Using these labor modules, we compute household level labor supply in terms of total hours worked per adult as well as labor supply for the farm and non-farm sectors. We then run similar fixed effects regressions to quantify the implication of temporal variation in night light intensity on households' overall labor supply as well as sector-specific labor supply to farming and non-farm activities.

The first two columns of Table 5 provide estimates on the implication of night light intensity on the overall household level labor supply per adult equivalence. The next two columns estimate similar equations for households' labor supply on farming activities while the last two columns provide similar estimates focusing on households' labor supply to non-farm activities. The results in the first two columns show that temporal dynamics in night light intensity is associated with higher labor supply. This suggests that urbanization may bring labor market opportunities to rural households and their members. Decomposing the overall effect to the farm and non-farm activities, the third and fourth columns show that night light intensity has no meaningful implication on households' labor supply to farm activities. On the other hand, the last two columns of Table 5 show that night light intensity is strongly and significantly associated with higher non-farm economic opportunities and hence associated labor supply. These patterns are intuitive as urban expansion is commonly associated with a shift in major economic activities from agriculture to non-farm activities.

In Table 6 we further decompose households' non-farm activities into non-farm business related and wage-related activities. This decomposition of these non-farm activities into wage-related and non-farm business activities shows that much of the overall effects are driven by wage-related economic opportunities. This is not surprising, given that our estimates are mostly short-term effects, while some of the non-farm business activities require longer periods to be realized.

Overall, these results suggest that urbanization may create labor market opportunities, especially those related to non-farm activities. These patterns are consistent with previous studies showing urbanization leads to shift in employment opportunities from agriculture to more remunerative non-farm employment opportunities (Bloom et al., 2008; Henderson, 2010; de Brauw and Mueller, 2012; Christiaensen et al., 2013). Following some other studies, these labor market opportunities are expected to lead higher income per capita (Dorosh and Thurlow, 2014) and more diversified income portfolio (Mezgebo and Porter, 2019).

Two features of our data and sample make our findings particularly interesting for African urban development programs and policy making. First, the type of urbanization we are studying in this paper is not the typical urbanization that leads to creation of major towns and cities, rather expansion of small rural towns. The significant welfare and labor market impacts of these small-scale urban growth is consistent with evolving studies highlighting the relatively higher impacts of growth of secondary towns (Christiaensen et al., 2013; Christiaensen and Kanbur. 2017; Gibson et al., 2017). Second, the time period and horizon we are studying is short and only two years, implying that much of the effects we document are short-term effects, which could cumulate in the longer term.

Table 5: Night light intensity and labor market outcomes

Explanatory Variables	(1) Working hours	(2) Working hours	(3) Working hours farm	(4) Working hours farm	(5) Working hours non-farm	(6) Working hours non-farm
NTL (mean)	0.358***	0.318***	0.131*	0.034	0.227***	0.284***
	(0.073)	(0.071)	(0.075)	(0.064)	(0.058)	(0.042)
Gender of household head	1.386***	-4.725	1.596***	-2.524	-0.210	-2.201
	(0.506)	(3.369)	(0.402)	(2.480)	(0.424)	(2.492)
Ln (age of household head)	-5.445***	-9.428**	-0.272	1.888	-5.172***	-11.316***
	(0.988)	(3.889)	(0.706)	(2.384)	(0.707)	(3.031)
Education head (dummy)	0.316	1.550	-1.155***	0.463	1.470***	1.087
	(0.473)	(1.100)	(0.323)	(0.773)	(0.388)	(0.738)
Household size	-0.779***	-1.820***	-0.458***	-0.785**	-0.321***	-1.035***
	(0.118)	(0.425)	(0.092)	(0.323)	(0.086)	(0.306)
Ln (average age in household)	4.116***	3.521**	0.685	1.760	3.432***	1.761
	(0.952)	(1.753)	(0.751)	(1.228)	(0.607)	(1.149)
Farm size (ha)	0.006	0.008	-0.010	-0.033	0.016	0.041
	(0.035)	(0.029)	(0.018)	(0.027)	(0.041)	(0.044)
Ln (TLU)	2.499***	0.889	3.688***	1.389***	-1.189***	-0.501
	(0.339)	(0.623)	(0.302)	(0.532)	(0.223)	(0.327)
Access to micro finance	-0.922	-1.066	-0.814	-0.986	-0.108	-0.080
	(1.306)	(1.284)	(1.050)	(1.027)	(0.824)	(0.803)
Access to formal credit	-0.302	-2.073*	0.624	-0.238	-0.926*	-1.834**
(borrowed from formal source)	(0.692)	(1.112)	(0.561)	(0.923)	(0.509)	(0.829)
Enumeration FE	Yes	Yes	Yes	Yes	Yes	Yes
HH fixed effects	No	Yes	No	Yes	No	Yes
R-squared	0.294	0.61	0.372	0.67	0.352	0.67
No. observations	6682	6682	6682	6682	6682	6682

Notes: NTL stands for night light intensity. In this table we are employing average night light intensity across a buffer zone of 10 square kilometres. Standard errors, clustered at enumeration area level, are given in parenthesis. $^{*}p< 0.10$, $^{**}p< 0.05$, $^{***}p< 0.01$.

Table 6: Night light intensity and labor market outcomes

Explanatory Variables	(1) Working hours business	(2) Working hours business	(3) Working hours wage	(4) Working hours wage
NTL (mean)	-0.089	-0.006	0.316***	0.290***
	(0.083)	(0.087)	(0.051)	(0.061)
Gender of household head	-0.419	-1.926	0.210	-0.274
	(0.342)	(2.403)	(0.218)	(0.451)
Ln (age of household head)	-4.149***	-12.299***	-1.023***	0.983
	(0.621)	(2.826)	(0.383)	(1.055)
Education head (dummy)	0.394	1.144*	1.076***	-0.058
	(0.311)	(0.681)	(0.231)	(0.332)
Household size	-0.144*	-0.997***	-0.177***	-0.038
	(0.073)	(0.298)	(0.043)	(0.131)
Ln (average age in household)	3.008***	2.546**	0.424	-0.785*
	(0.556)	(1.096)	(0.289)	(0.426)
Farm size (ha)	-0.015*	0.003	0.031	0.038
	(0.009)	(0.011)	(0.044)	(0.047)
Ln (TLU)	-0.800***	-0.544*	-0.389***	0.044
	(0.180)	(0.298)	(0.128)	(0.083)
Access to micro finance	-0.350	-0.457	0.242	0.377
	(0.850)	(0.796)	(0.294)	(0.279)
Access to formal credit	-0.652	-0.880	-0.274	-0.954**
(borrowed from formal source)	(0.395)	(0.692)	(0.271)	(0.455)
Enumeration FE	Yes	Yes	Yes	Yes
HH fixed effects	No	Yes	No	Yes
No. observations	6682	6682	6682	6682

Notes: NTL stands for night light intensity. In this table we are employing average night light intensity across a buffer zone of 10 kilometres square. Standard errors, clustered at enumeration area level, are given in parenthesis. $^{*}p< 0.10$, $^{**}p< 0.05$, $^{***}p< 0.01$.

6.2. Urbanization and welfare inequality

The relationship between urbanization and welfare inequality dates back to the classic Kuznets (1955) work, which showed an inverted U-shaped relationship between urbanization and income inequality. Kuznets (1955) argues that at early stages of development or urbanization, countries are more likely to experience higher income inequality and this trend is expected to decline as countries develop. This pattern has been tested in some countries and continents. Most recently, Kanbur and Zhuang (2013) show that such relationship and pattern exist among Asian countries. Berdegue et al. (2015) provide similar evidence for Latin America, mainly Chile and Colombia. However, these studies also highlight that the contribution of urbanization to national income inequality vastly vary across countries. Whether the Kuznets (1955) hypothesis holds in Africa, remains an unexplored empirical avenue.

In this section, we test for any relationship and causal link between urbanization and welfare inequality in Ethiopia. For this purpose, we compute Gini coefficients associated with enumeration areas and conduct fixed effect estimations. The estimates in Table 7 come from enumeration area-level fixed effect estimations. Each column indicates different measure and construction of night light intensity. The results in Table 7 show that night light intensity is significantly and positively associated with welfare inequality. The relationships remain consistent across all indicators of night light intensity. For instance, the first column shows that one unit (DN) additional increase in night light intensity is associated with about 0.007 increase in Gini coefficient. This confirms Kuznets (1955) long-existed theoretical hypothesis as well as recent anecdotal pieces of evidence insinuating that recent urban expansion trends in Ethiopia may not be benefiting all groups of societies (e.g., Broussard and Teklesellasie, 2012; Mezgebo, 2017). These types of patterns are expected to hold at early stages of urbanization when investments on infrastructure and institutions are limited (Balack and Henderson, 1999).

However, the size of the coefficients in Table 7 as well as the heterogeneity in impacts from our quintile regressions in Figure 2 deserve further scrutiny. The size of the coefficients in Table 7 are small, because relative to the mean night light intensity in our sample, increasing night light intensity by one digital number involves tripling current average night light intensities in our sample. Our quantile regressions in Figure 2 show that these potential heterogeneities in the impacts of urban expansion and hence associated welfare inequalities are driven by the pattern that those in the lower and higher welfare percentile are more likely to benefit from urban expansion than those in the middle welfare percentile. This implies that these potential welfare inequalities are mainly driven by those benefiting more than others, and not because some groups are negatively affected by urban expansion. These pieces of evidence may relieve potential concerns on the potential adverse impacts of urban expansion.

Table 7: Night light intensity and welfare inequality

	(1) Gini Coefficient	(2) Gini Coefficient	(3) Gini Coefficient
NTL (mean)	0.007***		
	(0.001)		
NTL (max)		0.002**	
		(0.001)	
NTL (sum)			0.000***
			(0.000)
Year dummy	Yes	Yes	Yes
Enumeration area FE	Yes	Yes	Yes
No. observations	635	635	635

Notes: NTL stands for night light intensity. The first column uses mean night light intensity. The second and third columns use maximum and total night light intensity, respectively. Standard errors are given in parenthesis. $^{*}p< 0.10$, $^{**}p< 0.05$, $^{***}p< 0.01$.

6.3 Urbanization and real price of food items

Despite the positive impacts shown in Section 5, urban expansion may also affect households' welfare negatively. Urban growth is often associated with increasing demand for food products. This increasing demand for food items, coupled with the usually inelastic supply of food items may trigger increase in prices for food items. While this increase in food prices may benefit rural producers, it can adversely affect urban dwellers disproportionally. We compile community level real price of food items (per kilogram), mostly crops, and run similar fixed effects regressions at village level. Some of the specifications in Table 8 control for enumeration area (village) level fixed effects while some of them capture food item fixed effects. All these estimates show temporal variations in night light intensity are associated with higher real prices of food items. This is consistent with the long-held view that urban growth may increase demand for food items, which in turn, triggers price rise. However, the size of the coefficients in Table 8 are appreciably small. These estimates show that increasing night light intensity by one unit (DN), which involves about tripling current average night light intensity in our sample, is associated with 0.2-0.5 percent increase in real price of food items. Thus, although the signs of our estimates are consistent with the existing theories and studies, the short-term impacts of urban expansion may be negligible. However, our estimates are short-term impacts of growth of small towns realized in two years. In the longer-term and at aggregate level, these increase in price of food items may cumulate and induce food price inflations with important macroeconomic implications. Thus, these results have important implications in terms of informing public debates on the inflationary implication of urban expansion.

Table 8: Night light Intensity and price of food items

Explanatory variables	(1) Log (real price per kg)	(2) Log (real price per kg)	(3) Log (real price per kg)
NTL (mean)	0.002**	0.005**	0.003***
	(0.001)	(0.002)	(0.001)
Year dummy	Yes	Yes	Yes
Region dummies	Yes	-	-
Enumeration area FE	No	Yes	-
Food item FE	No	No	Yes
No. observations	635	635	635

Notes: NTL stands for night light intensity. Standard errors, clustered at enumeration area level, are given in parenthesis. $^{*}p< 0.10$, $^{**}p< 0.05$, $^{***}p< 0.01$.

7. Robustness Exercises

In an attempt to probe the robustness of our main results, we conduct two important empirical exercises to address two identification threats. First, despite the fact that households have limited control over urban growth, they may endogenously sort their residence through migration decisions. Households may endogenously migrate to more urbanizing areas or to areas with higher labor market potential. In an attempt to explore whether such endogenous migration patterns are driving our main results, we restrict our sample to those households who have lived long in the area. We particularly exclude recent migrants and estimate similar regressions. Table 9 provides these estimates, which are literally similar to those based on full sample estimates. This suggests that much of the effects are not driven by endogenous selection and migration of some households.

Table 9: Night light Intensity and household welfare (excluding recently migrated households)

Explanatory Variables	(1) Log (real consumption)	(2) Log (real consumption)	(3) Log (real consumption)
NTL (mean)	0.015***	0.015***	0.019***
	(0.005)	(0.005)	(0.007)
Household characteristics	Yes	Yes	Yes
Enumeration area FE	No	Yes	Yes
HH fixed effects	No	No	Yes
Year dummies	Yes	Yes	Yes
R-squared	0.19	0.41	0.73

No. observations	5315	5315	5315

Notes: NTL stands for night light intensity. In this table we are employing mean night light intensity across a buffer zone of 10 kilometres square. Standard errors, clustered at enumeration area level, are given in parenthesis. $^{*}p< 0.10$, $^{**}p< 0.05$, $^{***}p< 0.01$.

Our second robustness exercise explores the role of omitted variables in confounding our causal impacts. Urbanization is a process that may correlate with other unobservable infrastructural and social developments. These omitted variables and trend may correlate with our measure of urbanization, night light intensity. To judge the stability of our estimates to some potentially omitted variables, we employ an empirical technique developed by Oster (2017) and estimate the lower and upper bounds of our estimates. Oster (2017) proposes assessing the stability of treatment effects by comparing impacts from an uncontrolled (baseline) specification with a more saturated specification. In Table 10 we provide lower and upper bounds of treatment effects associated with our four (significantly significant) outcome variables. The estimates from uncontrolled and controlled regression specifications are very similar, suggesting that omitted variables, including those which can be controlled in our specifications, have little implications and confounding role. This is not surprising given that we are relying on temporal variations in night light intensity, which can be reasonably argued to be exogenous to micro-level household decisions. All our main effects fall between these two bounds. This suggests that our results are less susceptible to omitted trends and variables correlated with our measure of urban growth.

Table 10: Lower and upper bounds of treatment effects using Oster (2017) approach

Outcome variable	(1) Uncontrolled (baseline) effects	(2) Controlled Effects
Log (real consumption)	0.016	0.019
Labor supply (total working hours per adult)	0.292	0.318
Labor supply (working hours non-farm)	0.267	0.284
Labor supply (working hours wage-related)	0.288	0.289

Notes: NTL stands for night light intensity. Standard errors, clustered at enumeration area level, are given in parenthesis. $^{*}p< 0.10$, $^{**}p< 0.05$, $^{***}p< 0.01$.

8. Conclusions

Despite evolving pieces of evidence showing that Africa is urbanizing differently (e.g., Jedwab, 2012; Henderson et al., 2013), empirical evaluations on the welfare implications of urban development programs in Africa are missing. In particular, the welfare implication of recent and remarkable urbanization trends in sub-Saharan Africa, including Ethiopia, remains unexplored. This is partly attributable to lack of objective measures of the level and dynamics of urbanization. Most previous measures and definitions of urbanization are based on aggregate and census-based indicators, which cannot sufficiently capture significant heterogeneities and short-term dynamics in urban expansion. Most of these census-based rural-urban indicators are unable to capture a continuum of rural-to-urban transformation at various stages and pace.

In this paper we explore the implication of urbanization on households' welfare and livelihood using objective markers of urbanization. Following recent successful attempts, we employ satellite-based night light intensity data to capture urban amenities and urban growth. For such a purpose, we link household-level longitudinal data with satellite-based night light intensity. We particularly apply this new marker of urbanization to identify and quantify the welfare implication of recent urbanization trends in Ethiopia. Urban development programs in Ethiopia provide an interesting case for some important reasons. Despite from a low base, urban growth in Ethiopia remains above the sub-Saharan African average and regulating urban expansion remains a top priority of the Ethiopian government. Indeed, the current government in Ethiopia remains sufficiently vigilant and committed to proactively manage and monitor current and future urban expansions. However, most of the policy discourses in this regard are not informed by rigorous evaluations, except for some anecdotal pieces of evidence providing mixed findings. In an attempt to inform these debates, we assemble geo-referenced and nationally representative household-level longitudinal datasets coming from the Living Standard Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) for Ethiopia. We exploit these longitudinal variations in our measure of urbanization and hence estimate household fixed effects models.

We find that urban growth, particularly expansion of small towns, as measured by night light intensity, is associated with household welfare improvement. This pattern holds for both ultimate measures of welfare, mainly consumption as well as intermediate welfare indicators, including labor market outcomes of households. We particularly find that one unit (digital number) increase in night light intensity is associated with about 2 percent improvement in household welfare. Similarly, night light intensity is significantly associated with improved labor market outcomes and opportunities. More specifically, urban growth improves households' engagement in non-farm economic activities. We also find significant heterogeneities in the impact of urban growth. Our quantile regressions show that those households at the lower and higher welfare percentile are more likely to benefit from urban growth than those in the middle welfare percentile.

However, we also find suggestive evidence insinuating that urbanization is associated with welfare inequality. We show that potential dynamics in urban expansion may trigger welfare inequality among households living in a specific community. Furthermore, we find that urban expansion is associated with increasing price of food items. We particularly show that temporal dynamics in night light intensity may increase demand for food items and hence price of these products. Nevertheless, the size of effects on welfare inequality and price of food items are marginal, implying that the positive welfare implications of urban expansion may outweigh.

Our results have important implications in terms of informing public policy debates on the consequences and implication of contemporary urban expansion. Our findings highlight that on average urban expansion can improve household welfare, particularly as it creates labor market opportunities that can improve households' income. However, such improvements may not be uniformly distributed as suggested by the heterogeneous impacts we document and the slightly higher inequality associated with urban expansion. The latter result highlights the trade-off associated with urban expansion, improving average welfare of households and increasing welfare inequality among households in a community. This trade-off reinforces the need to regulate and monitor existing urban expansion in Ethiopia in a way that can inclusively benefit larger groups of societies.

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Appendix

Table A1: Night light intensity and household welfare

Explanatory Variables	(1) Log (real consumption)	(2) Log (real consumption)	(3) Log (real consumption)	(4) Log (real consumption)
NTL (max or sum)	0.005*	0.007**	0.000*	0.000**
	(0.003)	(0.003)	(0.000)	(0.000)
Gender of household head	0.021	-0.028	0.022	-0.026
	(0.021)	(0.097)	(0.021)	(0.097)
Ln (age of household head)	-0.256***	-0.092	-0.255***	-0.085
	(0.036)	(0.143)	(0.036)	(0.143)
Education head (dummy)	0.129***	-0.006	0.128***	-0.008
	(0.020)	(0.038)	(0.020)	(0.038)
Household size	-0.061***	-0.054***	-0.061***	-0.054***
	(0.004)	(0.017)	(0.004)	(0.017)
Ln (average age in household)	0.251***	0.337***	0.250***	0.336***
	(0.035)	(0.058)	(0.035)	(0.059)
Farm size (ha)	0.003**	0.002	0.003**	0.002
	(0.001)	(0.001)	(0.001)	(0.001)
Urban (dummy)	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
ln(TLU)	0.110***	0.054**	0.111***	0.055**
	(0.013)	(0.021)	(0.013)	(0.021)
Non-farm income (dummy)	0.003	0.059*	0.003	0.059*
	(0.021)	(0.036)	(0.021)	(0.036)
Access to micro finance	0.055	0.053	0.052	0.048
	(0.058)	(0.059)	(0.058)	(0.058)
Access to formal credit	-0.004	-0.068	-0.004	-0.069
(borrowed from formal source)	(0.028)	(0.042)	(0.028)	(0.042)
Enumeration area FE	Yes	Yes	Yes	Yes
HH fixed effects	No	Yes	No	Yes
Year dummies	Yes	Yes	Yes	Yes
R-squared	0.412	0.73	0.412	0.73
No. Observations	6478	6478	6478	6478

Notes: NTL stands for night light intensity. In this table we are employing maximum and total night light intensity across a buffer zone of 10 kilometres square. The first two columns use maximum night light intensity while the last two columns use total (sum of) night light intensity. Standard errors, clustered at enumeration area level, are given in parenthesis. $^{*}p< 0.10$, $^{**}p< 0.05$, $^{***}p< 0.01$.