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Can Urbanization Improve Household Welfare? Evidence from Ethiopia

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Abstract

Despite evolving evidence that Africa is experiencing urbanization in a different way, empirical evaluations of the welfare implications of urban-development programs in Africa remain scant. We investigated the welfare implications of recent urbanization in rural areas and small towns in Ethiopia using household-level longitudinal data and satellite-based night-light intensity. Controlling for time-invariant unobserved heterogeneity (across individuals and localities) and exploiting intertemporal and interspatial variation in satellite-based night-light intensity, we found that urbanization, as measured by night-light intensity, was associated with significant welfare improvement. In particular, we found that a one-unit increase in night-light intensity was associated with an improvement in household welfare of about 2%. Much of this was driven by the increase in labor-market participation in the non-farm sector, mainly salaried employment, induced by urbanization. Other potential impact pathways, such as an increase in consumer prices or migration explained little (if any) of the change in household welfare. Finally, our quantile and inequality analyses suggested that the observed urbanization had a negligible effect on the distribution of household welfare. Our results can inform public policy debates on the consequences and implications of urban expansion in Africa.

Keyword: urbanization, night-light intensity, welfare, labor-market outcomes, Ethiopia, sub-Saharan Africa.

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I. Introduction

The world has experienced unprecedented levels of urbanization with the highest growth rates occurring in developing countries. Africa is expected to be the fastest urbanizing continent from 2020 to 2050 (United Nations, 2014). Urbanization involves major structural, socio-economic, and land-use transformations. Most urbanization processes generally involve large public and private investments in rural areas and small towns[1] and are generally combined with high economic growth. These processes and developments may take place differently across contexts and continents, however. For instance, many argue that Africa's urbanization trend remains distinct (Jedwab, 2012; Henderson, Roberts & Storeygard, 2013) and that Africa is urbanizing without structural transformation and industrialization (Fay & Opal., 2000; Jedwab, 2012; Jedwab & Vollrath, 2015; Gollin, Jedwab & Vollrath. (2016).[2] The pace of urbanization in many African countries has surpassed the levels of structural and political transformation that are required to accommodate rapid urban expansion, which has led to the proliferation of slums and informal sectors (World Bank, 2013).[3]

These rapid urbanization trends present new opportunities and challenges for ensuring sustainable and inclusive growth in Africa. Previous literature on urbanization has mostly focused on large cities and metropolitan areas. In the context of sub-Saharan African countries, poverty and youth unemployment have been considered the major challenges facing urban centers (African Development Bank, 2011). Recent studies have indicated two phenomena: poverty has been urbanizing (Ravallion, Chen & Sangraula, 2007) and, hence, becoming an urban phenomenon (Dorosh & Thurlow, 2014), and economic inequality has been growing in African urban centers (World Bank, 2013).

It has frequently been argued that the urbanization of poverty is driven by migration of the rural poor to urban areas, which is often associated with unplanned urbanization (Ravallion,

[1] In the context of Ethiopia, small towns are defined as those towns with a population smaller than 10,000.

[2] Urbanization in Africa is commonly linked to creation of ''consumer cities'' rather than ''producer cities'' that depend upon manufacturing sectors (Jedwab, 2013; Gollin, Jedwab & Vollrath, 2016)).

[3] This is reflected by the fact that 62% of urban residents in Africa live in slums with high and rising rates of youth unemployment (World Bank, 2013).

Chen & Sangraula, 2007; Elhadary & Samat, 2012) and the vulnerability of urban residents to climate shocks (Cohen & Garrett, 2010). In addition, urbanization is commonly linked to increasing demand for food products and public services. This increasing demand, coupled with less responsive (inelastic) food-production systems, can lead to an increase in consumer prices.[4]

Another important potential effect of urbanization is an increase in income inequality, particularly at early stages of development (Kuznets, 1955; Kanbur & Zhuang, 2013). This is particularly believed to be the case when investments in infrastructure and institutions are limited, a common pattern in many developing countries in which urban expansion has occurred (Black & Henderson, 1999). Recent urbanization trends in sub-Saharan Africa (SSA) are not accompanied by adequate investments and thus do not lead to required levels of industrialization (Jedwab, 2012; Henderson, Roberts & Storeygard, 2013; Gollin, Jedwab & Vollrath, 2016). This implies that the poorest households may gain little from emerging urbanization which can, in the short to medium term, increase income inequality.

On the other hand, some empirical studies have highlighted the positive effects of urban expansion, including long-term welfare implications (World Bank, 2009; Glaeser, 2011). Urbanization involves shifting employment opportunities from agriculture to more remunerative and productive industrial and non-farm employment (Bloom, Canning & Fink, 2008; Henderson, 2010; Diao, Magalhaes & Silver, 2019). Other studies have shown that urbanization improves market linkages by increasing demand for high-value agricultural products and non-farm employment (Cali & Menon, 2012; Datt, Ravallion & Murgai, 2016; Swain & Teufel, 2017; Arouri, Youssef & Nguyen-Viet, 2016; Vandercasteelen et al., 2018).

Urbanization has also been found to improve access to markets and thus may generate higher income to support rural livelihoods (Cali & Menon, 2012). Consistent with this channel, studies have indicated that urbanization rates are positively associated with higher per-capita income (Dorosh & Thurlow, 2014; Ravallion, Chen & Sangraula, 2007; Bloom, Canning & Fink, 2008) and a more diversified income portfolio (Mezgebo & Porter, in press). Urbanization may

[4] Urban dwellers are generally more vulnerable to price shocks (Alem & Söderbom, 2012).

also influence the welfare of rural households by enhancing investments in farming technologies and by creating market opportunities for agricultural products (Swain & Teufel, 2017). Urban expansion may encourage rural households to tailor their agricultural production in response to urban growth and, thus, to generate higher monetary returns (Stage, Stage & McGranahan, 2010; Vandercasteelen et al., 2018). Relatedly, a key feature of the urbanization process concerns the movement of people from remote and rural areas to urban areas, a trend that may affect the labor-market outcomes of urban and rural dwellers (e.g., Henderson, Storeygard & Deichmann, 2017).

The findings reported above do not necessarily apply to the urbanization that transforms rural areas and expands small towns. As Christiaensen and Kanbur (2017) reported, some preliminary evidence has suggested that small towns may contribute to poverty reduction and welfare improvements to a larger extent than do bigger cities. The growth of small towns can create non-farm employment and increase income opportunities for youth (de Brauw & Mueller, 2012). This may also shift the primary source of income and employment of rural households located near small towns (Diao, Magalhaes & Silver, 2019). Nevertheless, despite evolving evidence that Africa is experiencing urbanization in a different way, empirical evaluations of the welfare implications of urban-development programs in Africa are scarce. In particular, the implications for household welfare of urbanization trends in sub-Saharan African rural areas and small towns have not been well-explored. Additionally, as the short review above makes clear, urbanization can lead to positive or negative effects on various welfare dimensions, so its net effect on welfare depends upon whether positive or negative impacts prevail. Thus, whether urbanization improves overall household welfare remains far from settled.

The scarcity of empirical studies on the implications of urbanization can be attributed in part to lack of an objective measure of the level and dynamics of urbanization. Previous attempts to measure urbanization and urban growth have employed census-based rural-urban (binary) indicators, measures that were unable to capture potential heterogeneities among urban areas, the rapid temporal dynamics of urbanization, or potentially complex and nonlinear relationships between urbanization and household livelihoods (Champion & Hugo, 2004; Dahly

& Adair, 2007; Amare et al., 2018). Rather than exist as a binary phenomenon, urbanization involves a continuum of rural-to-urban transformations at various stages and speeds, so census-based indicators are less likely to capture evolving urbanization processes in areas officially categorized as rural.[5] Thus, alternative and reliable metrics of urbanization are crucial for exploring the implications of urbanization for household welfare and livelihood and for informing urban-development programs in Africa.

The advent of satellite-based night-light data have offered an interesting opportunity to measure urbanization and urban expansion. Given that night light remains a fundamental urban feature, night-light intensity is 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 in which measures and statistical indicators of urbanization are neither readily available nor standardized. Recent studies have successfully applied night-light-intensity data to the study of the implications of urbanization in Africa (Michalopoulos & Papaioannou, 2013; Storeygard, 2016; Abay & Amare, 2018; Amare et al., 2018).

We employed satellite-based night-light-intensity data as a marker of urban growth to study the short-term implications of urbanization on household welfare and livelihood in rural areas and small towns in Ethiopia. We were particularly interested in identifying whether recent urbanization trends in Ethiopia were improving household welfare. Urban-development programs in Ethiopia share most of the challenges that other African urban centers are facing.[6] Cognizant of this, the Ethiopian government has recently given attention to trends in urbanization (Federal Democratic Republic of Ethiopia, 2016). Indeed, the monitoring of trends in urban expansion has been incorporated into the Ethiopian government's Growth and Transformation Plan (GTP-II). Evolving urban growth in Ethiopia provides a unique opportunity to manage and regulate urban-development programs to ensure inclusive and sustainable growth.

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[5] Most censuses are conducted every five to ten years, which means they are less likely to capture short-term dynamics in urban expansion and associated developments.

[6] Annual urban growth in Ethiopia amounts to about 4.5%, which is higher than the sub-Saharan African average (World Bank, 2011).

Despite some attempts, the welfare implications of recent trends in urban expansions in Ethiopia remain unexplored. Indeed, some anecdotal evidence shows that trends in urban expansion in Ethiopia may not benefit all groups equally (e.g., Broussard & Teklesellasie, 2012; Mezgebo, 2017).

We assembled georeferenced and household-level longitudinal data from the 2011-2012 and 2013-2014 Living Standard Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) for Ethiopia. The LSMS-ISA household surveys followed the same households across time, providing longitudinal variation in our measure of urban expansion as well as data on household welfare and livelihood. We merged these longitudinal household data with satellite-based time series night-light-intensity data from the U.S. Defense Meteorological Satellite Program Operational Linescan System (DMSP-OLS), measured at the enumeration area (EA) level. By exploiting the exogenous spatial and temporal dimensions (i.e., across and within EA) variations in urban expansion (night-light intensity) and controlling for unobserved individual and community heterogeneity, we examined the welfare implications of such dynamics in urbanization. Because our sample consisted of rural and small towns, we focused on the expansion of small towns and examined the implications of these dynamics on household welfare.

We found that urban growth, mainly the expansion of small towns, as measured by night-light intensity, had a positive short-term effect on household welfare. We particularly found that a one-unit (digital number) increase in night-light intensity was associated with about a 2% improvement in household welfare. Our findings are related to literature that has identified the effects of the expansion of small towns on household welfare (Christiaensen, De Weerdt & Todo, 2013; Christiaensen & Kanbur, 2017; Gibson et al., 2017). The driving mechanism appears to be the resulting increase in household participation in the non-farm sector and particularly in salaried employment. This is in line with what is expected from urbanization and associated rural structural transformations that may expand non-farm economies and sectors. The rise in consumer prices, as well as migration, both of which are possible effects of urbanization, appear to play a marginal role, if any.

We also found suggestive evidence that dynamics in urban expansion may slightly trigger welfare inequality among households in a specific community while also increasing the real price of food. Our quintile and inequality regressions suggested that households in higher consumption quintiles enjoyed slightly higher welfare gains from urban growth. Nevertheless, the size of the effect on welfare inequality was marginal, implying that the aforementioned positive welfare impact of urban expansion may outweigh the negative effects associated with a rise in inequality.

Our results can inform public policy on the consequences and implications of urban expansion in Africa. It is worth noting, however, that urbanization may involve other structural transitions that complicate the identification of potential channels through which urbanization can affect household welfare and labor-market outcomes. Thus, the channels we discuss here and explored in our empirical exercise are probably not sufficiently exhaustive. In addition, as we discuss below, our sample consisted of rural and small towns, implying that the type of urbanization we studied may be distinct from the typical urbanization that involves the creation of major towns and cities and which may have slightly different implications regarding the expansion of small towns (Christiaensen, De Weerdt & Todo, 2013; Christiaensen & Kanbur. 2017; Gibson et al., 2017).

II. Data and Measurement of Key Variables

2.1 Data and Descriptive Statistics

We used two different data sources: the Living Standard Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) for Ethiopia,[7] also known as the Ethiopia Socioeconomic

[7] The World Bank LSMS-ISA initiative provided financial and technical support to the Central Statistical Agency of Ethiopia in designing and implementing the survey and analysing and disseminating survey results.

Survey (ESS), and satellite-based night-light-intensity data gathered by the U.S. Defense Meteorological Satellite Program Operational Linescan System (DMSP-OLS). The ESS data are longitudinal datasets collected every two years and cover a wide range of topics related to the consumption decisions of rural and urban households and to their production. More importantly, the ESS data provide georeferenced enumeration areas (EA).[8] These features allowed us to merge ESS data with the DMSP-OLS night-light-intensity data using georeferences.

We used two waves of the ESS for Ethiopia: the first was conducted in 2011-2012 and the second in 2013-2014. In the first wave, which covered only rural areas and small towns, members of a sample of households in 333 EAs throughout all Ethiopian states were interviewed. The second round re-interviewed members of the 2011-2012 sample households, including in major towns and cities, increasing the sample to 433 EAs.[9] Thus, the first round was representative of rural and small towns of Ethiopia while the second round was representative of the whole country.

We employed Version 4 of the DMSP-OLS time series for the night-light data, which covers only 1992 through 2013. For this reason, we did not use the latest and more recent round of the ESS (collected in 2015). We delineated a $10km^2$ zone around ESS enumeration areas and then extracted mean and maximum night-light intensities associated with the survey sites. Table 1 provides descriptive statistics of household and community-level characteristics. We mainly report the basic demographic and socioeconomic characteristics of households' whose members were expected to influence consumption and production decisions. We disaggregated and presented these descriptive figures across the two waves.

Because the first round covered only rural areas and small towns, our final sample excluded households from large towns that had joined in the second round. Thus, our final sample was representative of rural areas and small towns of Ethiopia. This implies that the type

[8] In the context of Ethiopia, an enumeration area covers about 150-200 households in rural areas and 150-200 housing units in urban areas.
[9] The Central Statistics Agency (CSA) defines small town as urban areas with a population of less than 10,000. Large towns are those with a population of 10,000 and above.

of urbanization on which we are reporting here mostly involves expansion of small rural towns, which is slightly different from the usual large-scale creation of large towns and cities. The summary statistics given in Table 1 remained comparable across both rounds. For instance, for the first round, households headed by women represented 25% of our sample, while this share amounted to 26% in the second wave. For most variables, the means and standard deviations were comparable across both rounds. The census-based urbanization indicator, the urban dummy, remained the same in both rounds, implying that these types of aggregate indicators could not capture short-term urbanization trends and dynamics. Again, the rural-urban census-based indicator showed that our study involved the implications of slight expansion and growth in small towns in mostly rural areas, though night-light intensities can capture even these small changes in urban growth. Furthermore, as we focused on two rounds and, as a consequence, urban expansion over a two-year span, any potential impacts of urban expansion were short-term.

Table 1: Summary Statistics of Sample Households

	2011 round		2013 round	
Household and community characteristics	**Mean**	**SD**	**Mean**	**SD**
Head of household is a woman	0.25	0.43	0.26	0.44
Age of head of household	44.01	15.73	45.81	15.32
Head of household attended school (0/1)	1.63	0.48	1.64	0.48
Household size	4.81	2.37	5.54	2.51
Household size in adult equivalence	3.87	1.95	3.97	1.92
Average age of household	27.29	12.02	24.55	12.12
Farm size (ha)	0.89	1.69	1.17	3.4
Livestock (TLU)	3.43	5.54	3.97	5.2
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
No. observations	3611		3513	

Source: Authors' calculations based on data from the ESS 2011 and 2013 for rural areas and small towns.

2.2 Defining and Describing Welfare and Related Outcomes

We used real consumption spending as a proxy for household welfare. Consumption spending included all home-produced and purchased food items consumed by the household.[10] We adjusted consumption spending to 2011 prices using spatial and temporal consumer-price indices (to convert nominal to real consumption). In particular, we employed the spatial (regional) price index provided by the World Bank in the ESS data and the temporal consumer price index (CPI) provided by the Ethiopian Central Statistics Agency (CSA) to ensure that our monetary variables were comparable across regions and years. To account for the household's age and sex composition, consumption spending was reported in adult scales using the indices available in the ESS dataset.

Table 2 provides summary statistics associated with our welfare indicators. We disaggregated and presented these figures for rural areas and small towns (as defined by the census). Households' real consumption spending decreased over the years, both for households in rural areas and small towns, and this is the result of the large increase in consumption prices during this period,[11] despite some increase in nominal consumption.

This is consistent with other recent studies that have investigated the welfare dynamics of Ethiopian households using similar data (e.g., Fuje, 2018). As expected, consumption remained higher in households located in small towns compared to those located in rural areas. Household members in small towns and urban areas spent a relatively larger share of their income on non-food items. This was not surprising given that households in small towns and urban centers have better access to services such as power, communication, schools, and sanitation services.

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 were reasonably

[10] Local prices were applied to value consumption of home-produced foods.

[11] The overall CPI for December 2013 amounted to 123.8, with food and non-food CPI amounting to 121.9 and 125.9, respectively.

comparable across both rounds, partly attributable to the similar timing of data collection. As expected, farming activities were prevalent in rural areas while non-farm activities were mostly practiced in small towns.

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
Nominal annual consumption per adult equivalence (ETB)	5248.8	6971.6	5314.9	7647.0
Real annual consumption per adult equivalence (ETB)	5317.9	7183.6	4325.4	6329.1
Food consumption per adult equivalence (ETB)	4361.5	4773.2	3460.6	4189.1
Non-food consumption (ETB)	850.9	2059.4	834.7	1774.3
Labor supply and labor market indicators				
Total hours worked over the previous seven days (per adult)	18.7	22.5	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)	5.7	19.8	2.3	14.6
Hours worked on business activities (per adult)	5.1	15.1	1.5	9.5
Hours worked on wage-related activities (per adult)	0.6	4.6	0.8	5.1
No. Observations	3,103	471	2,948	436

Source: Authors' calculations based on data from the ESS 2011 and 2013 for rural and small towns.
Notes: Consumption values were deflated using temporal and spatial price index deflators. Real consumption values are expressed in 2011 prices and reported in Ethiopian birr (ETB). 1 USD=17.29 ETB in 2011. Labor-supply and labor-market outcomes of households were measured in hours worked over the previous seven days and computed per adult household members (as estimated by the World Bank). All values are weighted by population sampling weights in our data.

2.3 Defining and Measuring Urbanization and Urban Growth

Despite unprecedented levels of rural-to-urban transformation in developing countries today, researchers and urban planners are still seeking more accurate measures of the level and dynamics of urbanization. Most measures of urban expansion, which are usually binary rural-urban indicators, come from population censuses and are therefore inadequate to capture the rapid dynamics of urban expansion. Most of these indicators are aggregated at higher levels, inhibiting micro-level analysis of the impact of urbanization on the livelihoods of households. Because most census-based indicators are constructed every ten years, this measurement problem is not unique to developing countries.[12]

These measurement challenges have encouraged researchers and urban planners to look for alternative measures or markers of urbanization. More recently, efforts have focused on constructing continuous and disaggregated indicators that can capture micro-level variations in urban expansion. For this purpose, satellite-based night-light intensity data has attracted a great deal of attention because of its potential to capture the dynamics of urbanization and related economic activities. Because access to electricity and lights remain key urban amenities, urban areas are expected to have higher night-light intensities 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, Taylor & Elvidge, 2010; Storeygard, 2016; Amare et al., 2018; Abay & Amare, 2018).

Following this trend, we measured urbanization and urban growth by using night-light intensity from remote-sensing data. This variable provided a continuous marker of the temporal dynamics of the urbanization process. Satellite-based luminosity data came 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-kilometer resolution. These data are further processed by the National Geophysical Data Center (NGDC) of the U.S. National Oceanic and Atmospheric Administration (NOAA). The luminosity data measure and express light intensity in digital numbers (DNs) ranging from 0 (no light) to 63 (highest light) for each square-kilometer pixel.[13]

We employed Version 4 of the DMSP-OLS time series, which covered only 1992 through 2013. A 10km^2 zone was delineated around ESS enumeration areas, and we extracted mean night-light intensities as well as maximum night-light intensities associated with these locations. After 2013, another version of the luminosity data, Version 1 VIIRS Night-Light series,

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

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

was introduced. However, the DMSP-OLS (1992-2013) and VIIRS night light data are not directly comparable because of differences in spatial resolution.

Luminosity data have novel features that are helpful for mapping urban growth. Most importantly, the longitudinal nature of these data and their availability at high spatial resolution allowed us to trace the dynamics of urbanization at a micro-level. In spite of the increasing use of night-light intensity to approximate the levels and dynamics of urbanization, these data suffer from some limitations (see Donaldson & Storeygard, 2016; Michalopoulos & Papaioannou, 2018). First, although less relevant to our context, night-light intensity data are censored at higher levels of the distribution, implying that these data may understate the level of light intensity 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 from light produced by activities such as gas production (Elvidge et al., 2009).[14] Considering our context, our luminosity data were highly skewed to the left, mainly because many parts of the developing world are dark (Michalopoulos & Papaioannou, 2018). This is the case in our context because our household level data covered a large part of rural Ethiopia. As we show in our estimations, however, these skewed luminosity data provided more variation and dynamics than the commonly used rural-urban indicator.

We merged the longitudinal ESS with the satellite-based night-light-intensity data from the DMSP-OLS.[15] Table 3 provides the dynamics of these indicators of urbanization. Starting from a low level, the average, maximum, and total night-light intensity increased over the two-year period from 2011 to 2013; average night-light intensity, for instance, increased by about 20%. Figure 1 provides the distribution of night-light intensity across both waves. This figure shows that the share of low night-light intensity decreased while the share of high-intensity categories increased across waves. For instance, the proportion of enumeration areas with zero

[14] Third, the luminosity data do not distinguish differences in light intensity caused by variations in infrastructure (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).

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

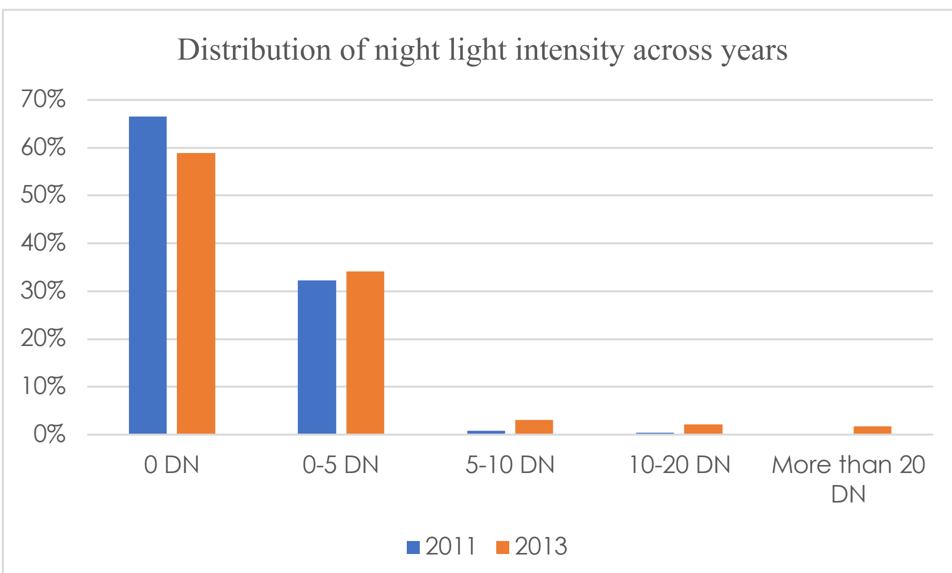
DN night light in 2011 was 67% and shrank to 59% in 2013. Given the Ethiopian government's recent investments in infrastructure, this was not surprising. We explored whether these dynamics in these indicators of urbanization could predict and cause potential welfare improvements.

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 night-light intensity (DN)	80.71	357.97	104.13	663.12

Source: Authors' calculations based on DMSP-OLS data.
Notes: Night-light intensity was measured using digital numbers (DN).

Figure 1: Distribution of Night-Light Intensity Across Years



Source: Authors' calculations based on DMSP-OLS data.
Notes: Night-light intensity was measured using digital numbers (DN).

III. Identifying the Impact of Urbanization on Welfare: Empirical Strategy

3.1 Econometric Specifications

Quantifying the impact of urbanization poses several empirical challenges, including endogeneity problems arising from omitted attributes and measurement problems. This was to be expected given that most urbanization programs are accompanied by economic growth that can influence overall livelihood. In light of this, we used an individual panel dataset and employed alternative econometric approaches that exploited the within (temporal) and across (spatial) exogenous variation of EAs as well as controlled for fixed unobserved individual heterogeneity and heterogeneity in EAs.

Because we conducted our analysis at the household level, potential dynamics in urbanization could have been exogenous to short-term livelihood outcomes. Hence, we exploited 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 was a relatively conservative approach because it required reasonable variations in our measure of urbanization across time.

We employed consumption values, specifically real consumption per adult equivalence, as our direct measure of welfare. Thus, our estimable welfare function was as specified below:

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

where $\ln C_{hvt}$ indicates logarithmic values of real consumption per adult equivalence for household *h* residing in an enumeration area (EA),*v* indicates period *t*, U_{vt} stands for the level of urbanization for each enumeration area (village) and time, while H_{hvt} captures additional household and village time-varying characteristics. δ_h and δ_t represent household- and time-fixed effects, respectively. The specification in Equation 1 was immune to time-invariant household and village-level heterogeneities. In the absence of time-varying unobservable factors that affect both consumption and urbanization, β_1 identifies the effect of urban growth on household welfare. Given the short period of time covered in our analyses, as well as the use of a relatively large number of time-varying control variables at the EA level that may have been be correlated with variations in our key variables, we are fairly confident of the reliability of our estimated causal relationship. In particular, given that households have little influence on urban expansion, we argue that the empirical specification in Equation 1 is reasonably able to identify the impact of urbanization on household welfare. One may still imagine, however, that some dynamic shocks and government interventions could simultaneously affect urban-development programs and household welfare. To minimize such contemporaneous shocks to our outcomes and the explanatory variables, we controlled for additional community-level attributes. We also considered alternative construction of our measure of urbanization. We computed average, maximum, and total night-light intensity in a specific enumeration area. Our key variables of interest varied at the village (enumeration area) level, implying that households in the same village may have shared some unobserved effects. Thus, in all our estimations, we clustered standard errors at the village level. In addition, we carried out the empirical test developed by Oster (2019) to assess the role of omitted variables in confounding the impact of urbanization on household welfare.

Besides quantifying the overall impact of urbanization on household welfare, we also explored both potential mechanisms and additional effects of urbanization on welfare distribution. First, as one important channel through which urbanization can improve household welfare, we estimated the implications of night-light intensity on the labor-market outcomes of various households. Although households have limited control over urban growth, their members might migrate to areas in which greater urbanization is taking place or to those with higher labor-market potential. We explored this second channel by dropping those who migrated between 2011 and 2013. That is, we tested whether the effect went (mostly or only) through migration or whether urbanization affected household welfare independently of migration. We note that this exercise additionally served to rule out potential biases due to endogenous migration decisions and unobserved heterogeneity which may have linked urbanization to the decision to migrate. In addition, to further circumvent endogenous dynamic migration decisions, we controlled for additional variables, including family size, as well as other time-varying factors. Third, we assessed the effect of urbanization on consumer prices, which are direct determinants of household welfare.

Furthermore, we investigated the impact of urbanization on welfare distribution. For this purpose, we estimated the effect of urban expansion on welfare inequality at the EA level.[16] We also estimated quantile fixed-effects regressions to identify the type of households enjoying higher (lower) benefits associated with urban expansion. In particular, we employed the fixed-effect regression method developed by Parente and Santos Silva (2016).

Estimation Results: Main Specification

Before presenting our main results, the following clarifications are in order. Our outcome variable was expressed as the logarithmic transformation of real consumption per adult equivalence. Our proxy for urbanization was night-light intensity. We constructed average, maximum, and total night-light intensities associated with each enumeration area. Night-light intensity was measured and expressed in digital numbers (DNs), which ranged 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 areas. The first two columns provide unconditional relationships between longitudinal variation in night-light intensity and household welfare. In the first column, we show results of controlling for enumeration-area fixed effects while the second column shows the effects of controls for household fixed effects. Enumeration area fixed effects can capture time-invariant community-level heterogeneities across space. Similarly, household fixed effects control for time-invariant household-level heterogeneities among households. As a result, we exploited longitudinal variations in urbanization to identify the impact of urban growth on welfare. Our outcome variable was 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) positively affected consumption per per-adult-equivalence. More specifically, a 1 DN

[16] We conducted village-level analyses of economic inequality and estimated Equation 1 at the enumeration-area (village) level.

increase in night-light intensity was associated with about a 2% increase in household consumption. As shown in the last two columns, the effects remained robust even after controlling for important time-varying covariates. Given the low level of light intensity in our sample, the size of the effect was plausible. These impacts were particularly considerable given the overall downward trend in real household welfare observed in our data and in other Ethiopian studies that have employed 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 followed similar specifications as in Table 4 and, as a result, all estimates controlled for some form of fixed effects, whether at the enumeration area- or household level. The first two columns are based on maximum night-light intensity while the last two employ total (sum) night-light intensity associated with a specific enumeration area (the delineated 10km^2 buffer zone). These results confirm those in Table 4, implying that the maximum or total night-light intensity around a specific location was associated with higher household welfare.

Besides highlighting the welfare implications 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 included census-based measures of urbanization using an indicator variable for urban areas. Despite capturing significant spatial variations in consumption among households, this indicator showed few or no temporal dynamics and hence vanished in our fixed-effects estimations. This implies that our measure of urbanization, night-light intensity, captured the short-term effects of urbanization and associated trends, which could otherwise not be captured by conventional census-based indicators of urbanization. This was particularly encouraging from a measurement point of view.

The signs and relationships between the other variables of interest and household welfare were consistent with our expectations and previous evidence. Focusing on the fixed effects estimates in Column 3 of Table 4, larger household size was associated with lower welfare. However, the composition of households seemed to be important. Increasing the average age of household members was associated with higher welfare. This was not surprising as an increase in the average age of household members implies more working hands to generate income. As expected, asset ownership predicted higher welfare as shown by the positive association between livestock ownership and household welfare. Those households with non-farm income had higher welfare.

Table 4: 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 (mean)	0.021*** (0.005)	0.024*** (0.008)	0.021*** (0.006)	0.024*** (0.008)
Sex of head of household			0.021 (0.027)	-0.097 (0.129)
Ln(age of head of household)			-0.237*** (0.047)	-0.019 (0.257)
Education head (dummy)			0.097*** (0.024)	-0.033 (0.080)
Household size			-0.061*** (0.006)	-0.049 (0.032)
Ln(average age in household)			0.241*** (0.046)	0.401*** (0.113)
Farm size (ha)			0.002*** (0.001)	0.001 (0.001)
Urban (dummy)			0.000 (0.000)	0.000 (0.000)
Ln(TLU)			0.125*** (0.017)	0.058 (0.039)
Non-farm income (dummy)			-0.058** (0.029)	0.035 (0.064)
Access to micro finance			0.079 (0.087)	0.069 (0.125)
Access to formal credit (borrowed from formal source)			-0.017 (0.034)	-0.051 (0.080)
Enumeration area FE	Ye	-	Yes	-
Household fixed effects	No	Yes	No	Yes
Year dummies	Yes	Yes	Yes	Yes
R-squared	0.336	0.730	0.411	0.747
No. observations	6753	6753	6478	6478

Source: Authors' calculations based on data from the ESS 2011 and 2013 for rural and small towns.
Notes: NTL stands for night-light intensity. In this table we employed mean night-light intensity across a buffer zone of 10km^2. Estimates were adjusted for sampling weights. Standard errors, clustered at the enumeration-area level, are given in parenthesis. $^*p< 0.10$, $^{**}p< 0.05$, $^{***}p< 0.01$.

IV. Potential Mechanisms

4.1 Urbanization and Households' Labor-Market Outcomes

Following the discussion of potential channels and mechanisms through which urbanization can affect household welfare, we explored and tested the proposed channels. One of the key channels identified in the literature is related to the impact of urbanization on labor productivity and, therefore, on households' labor-market outcomes.[17] We therefore explored the impact of night-light intensity on households' labor-market outcomes. The ESS data provided information on time-use and labor-allocation outcomes for all household members and for the previous seven days. Using these data, we computed the household-level labor supply in terms of total hours worked per adult and as labor supply for the farm and non-farm sectors. We then ran similar fixed-effects regressions to quantify the implications of temporal variations in night-light intensity on households' overall labor supply as well as on sector-specific labor supply (farming and non-farm activities, in particular).

The first two columns of Table 5 provide estimates regarding the implications of night-light intensity on overall household-level labor supply per adult equivalence. The next two columns estimate similar equations for farming activities, while the last two columns provide estimates that focus on non-farm activities. The results in the first two columns show that temporal dynamics in night-light intensity positively affected labor supply. This suggests that urbanization may bring labor-market opportunities to households and their members. Decomposing the overall effect of labor supply on farm and non-farm activities, the third and fourth columns show that night-light intensity had no meaningful implications for household-labor supply on farm activities. On the other hand, the last two columns of Table 5 show that night-light intensity strongly and significantly generated higher non-farm economic

[17] As mentioned earlier, another potential mechanism is migration. Because migration decisions may also concern identification (i.e., endogenous selection), we discuss it along with robustness checks in Subsection 6.2.

opportunities and hence increased associated labor supply. These patterns are intuitive because urban expansion is commonly associated with a shift in major economic activities from agriculture to non-farm. This shift in economic activities may improve overall productivity in the farm and non-farm sectors.

In Table 6, we show the results of further decomposing household non-farm activities into non-farm-business-related and wage-related activities, showing that much of the overall effect was driven by wage-related economic opportunities. This was not surprising, given that our estimates reflected mostly short-term effects, while some non-farm business activities required longer periods to be captured. Furthermore, the type of urbanization we studied as well as our time horizon may not have made it possible for individuals to start and run major non-farm businesses.

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 that have shown how urbanization leads to shifts in employment opportunities from agriculture to more remunerative non-farm employment opportunities (Bloom, Canning & Fink, 2008; de Brauw and Mueller, 2012; Christiaensen, De Weerdt & Todo, 2013). As other studies have shown, these labor market opportunities were expected to lead to higher per-capita income (Dorosh & Thurlow, 2014) and a more diversified income portfolio (Mezgebo & Porter, in press).

Two features of our data and sample make our findings particularly interesting for African urban-development programs and policy. First, the type of urbanization we studied is not the kind of urbanization that typically leads to the creation of major towns and cities but rather to the expansion of small towns. The significant welfare and labor market impacts of this small-scale urban growth were consistent with studies highlighting the relatively higher impacts of growth on secondary towns (Christiaensen, De Weerdt & Todo, 2013; Christiaensen & Kanbur, 2017; Gibson et al., 2017). Second, the time period and horizon of our study was only two years, and many of the effects we documented were short-term, though they could accumulate over 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)	0.601***	0.530**	0.223***	0.128	0.378***	0.402***
	(0.154)	(0.227)	(0.066)	(0.107)	(0.105)	(0.141)
Sex of head of household	1.258**	-4.553	1.266**	-3.391	-0.008	-1.161
	(0.593)	(5.218)	(0.598)	(5.831)	(0.490)	(3.637)
Ln(age of head of household)	-2.937**	-1.890	-0.980	-0.317	-1.957***	-1.573
	(1.170)	(5.433)	(1.052)	(4.700)	(0.697)	(3.567)
Education head (dummy)	-0.364	-0.646	-1.008**	-0.839	0.644*	0.194
	(0.598)	(1.904)	(0.459)	(1.564)	(0.342)	(1.041)
Household size	-0.828***	-1.181	-0.480***	-0.519	-0.348***	-0.661
	(0.134)	(0.783)	(0.132)	(0.694)	(0.099)	(0.447)
Ln(average age in household)	1.463	-0.663	0.563	1.002	0.900	-1.665
	(1.076)	(3.171)	(1.052)	(2.581)	(0.692)	(1.930)
Farm size (ha)	0.003	0.007	-0.013	-0.033	0.016	0.040
	(0.023)	(0.024)	(0.014)	(0.037)	(0.032)	(0.048)
Ln(TLU)	2.842***	1.601	3.812***	1.661*	-0.970***	-0.060
	(0.360)	(0.978)	(0.392)	(0.933)	(0.256)	(0.497)
Access to micro finance	-2.122	-2.176	-1.159	-1.382	-0.963	-0.794
	(1.737)	(2.471)	(1.587)	(2.195)	(0.772)	(1.156)
Access to formal credit	0.127	-0.540	0.382	0.087	-0.254	-0.627
(borrowed from formal source)	(0.749)	(1.655)	(0.842)	(1.726)	(0.435)	(1.144)
Enumeration FE	Yes	-	Yes	-	Yes	-
Household fixed effects	No	Yes	No	Yes	No	Yes
R-squared	0.339	0.673	0.388	0.707	0.322	0.698
No. observations	6682	6682	6682	6682	6682	6682

Source: Authors' calculations based on data from the ESS 2011 and 2013 for rural and small towns.
Notes: NTL stands for night-light intensity. In this table we employed average night-light intensity across a buffer zone of 10km^2. Working hours are in per-adult terms. Estimates were adjusted for sampling weights. Standard errors, clustered at the 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)	0.173	0.201	0.205***	0.201**
	(0.154)	(0.217)	(0.054)	(0.084)
Sex of head of household	-0.230	-1.385	0.222	0.223
	(0.432)	(3.554)	(0.186)	(0.510)
Ln(age of head of household)	-0.928	-1.300	-1.029***	-0.273
	(0.631)	(3.388)	(0.318)	(0.861)
Education head (dummy)	0.144	0.289	0.500***	-0.096
	(0.285)	(1.004)	(0.172)	(0.350)
Household size	-0.250***	-0.470	-0.098**	-0.191
	(0.087)	(0.421)	(0.038)	(0.155)
Ln(average age in household)	0.269	-1.524	0.631**	-0.140
	(0.612)	(1.723)	(0.301)	(0.681)
Farm size (ha)	-0.007	0.008	0.023	0.031
	(0.008)	(0.019)	(0.038)	(0.064)
Ln(TLU)	-0.610***	0.024	-0.360***	-0.084
	(0.235)	(0.436)	(0.110)	(0.183)
Access to micro finance	-1.340*	-1.234	0.377	0.440
	(0.791)	(1.157)	(0.419)	(0.593)
Access to formal credit	-0.033	0.058	-0.221	-0.685
(borrowed from formal source)	(0.368)	(0.928)	(0.196)	(0.643)
Enumeration FE	Yes	--	Yes	--
Household fixed effects	No	Yes	No	Yes
No. observations	6682	6682	6682	6682

Source: Authors' calculations based on data from the ESS 2011 and 2013 for rural and small towns.
Notes: NTL stands for night-light intensity. In this table we employed average night-light intensity across a buffer zone of 10km^2. Estimates were adjusted for population weights. Standard errors, clustered at the enumeration-area level, are given in parenthesis. $^*p< 0.10$, $^{**}p< 0.05$, $^{***}p< 0.01$.

4.2 Urbanization and Real Price of Food Items

Despite the positive impacts shown in Section 4, urban expansion may also negatively affect household welfare. Urban growth is often associated with increased demand for food products. This demand, coupled with a usually inelastic food supply may trigger increases in food prices. While an increase in food prices may benefit rural producers, it can adversely and disproportionally affect urban dwellers. We compiled community-level real food prices (per kilogram), mostly crops, and ran similar fixed-effects regressions at the village level. Some of the specifications in Table 7 controlled for enumeration area-level (village) fixed effects while some captured food-item fixed effects. All these estimates show that temporal variations in night-light intensity were 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 increases. The size of the coefficients in Table 7 is appreciably small, however. These estimates show that an increase of one unit (DN) in night-light intensity (which, in our sample, would have involved roughly tripling the current average night-light intensity) was associated with a 0.2-0.5% increase in the real the price of food items. Thus, although the signs of our estimates were consistent with existing theories and studies, the short-term impacts of urban expansion may be negligible. In the longer-term and aggregate levels, increases in the price of food may accumulate and induce food-price inflation with important macroeconomic implications. These results can inform public debate regarding the inflationary implications of urban expansion.

Table 7: Night-Light Intensity and the 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** (0.001)	0.005** (0.002)	0.003*** (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

Source: Authors' calculations based on data from the ESS 2011 and 2013 for rural and small towns.
Notes: NTL stands for night-light intensity. Standard errors, clustered at the enumeration-area level, are given in parenthesis. $^{*}p< 0.10$, $^{**}p< 0.05$, $^{***}p< 0.01$.

V. Additional Investigations and Robustness Checks

5.1 Urbanization, Welfare Inequality, and Poverty Decomposition

The relationship between urbanization and welfare inequality dates back to Kuznets' classic 1955 work, which documented an inverted U-shaped relationship between urbanization and income inequality. Kuznets (1955) argued that, at early stages of development or urbanization, countries were more likely to experience higher income inequality, a trend that would be expected to decline as countries developed. This pattern has been tested in some countries and continents. Most recently, Kanbur and Zhuang (2013) showed that such a relationship existed in Asian countries. Berdegue et al. (2015) provided similar evidence for Latin America, mainly Chile and Colombia. These studies also highlighted the fact that the contribution of urbanization to national income inequality varied vastly across countries. Whether the Kuznets' hypothesis holds in Africa remains unexplored.

For the purposes of testing for any relationship between urbanization and welfare inequality in Ethiopia, we computed Gini coefficients associated with enumeration areas and conducted fixed-effect estimations; the estimations are reported in Table 8. Each column indicates a different measure and construction of night-light intensity. The results in Table 8 show that night-light intensity was significantly and positively associated with welfare inequality. The relationships remained consistent across all indicators of night-light intensity. For instance, the first column shows that an increase of one unit (DN) of night-light intensity was associated with about a 0.007 increase in Gini coefficient. This confirms Kuznets' (1955) theoretical hypothesis as well as recent anecdotal evidence suggesting that contemporary urban expansion trends in Ethiopia may not benefit all groups (e.g., Broussard & Teklesellasie, 2012; Mezgebo, 2017).These patterns are expected to hold at early stages of urbanization when investments on infrastructure and institutions are limited (Black & Henderson, 1999). In a separate analysis based on the estimation reported in Column 3 of Table 4, we also decomposed the 2011-2013 variation in the Gini index and found that urbanization increased inequality by 0.4 points (significant at 10%), while no effect on poverty was found.[18]

In order to uncover potential heterogeneities in the impact of night-light intensity (urbanization) on household welfare, we also estimated quantile-regression specifications at the household level. Figure 2 provides the effects of night-light intensity across the welfare percentiles. These estimates suggested a slightly increasing trend and effect across welfare percentiles. For instance, the impact of urbanization on the richest 20th welfare percentile was slightly higher than the impact on the poorest 20th percentile. Households in the lower (up to the 30th percentile) and higher (from the 60th) welfare percentiles were more likely to benefit from urban expansion while the effect for those in the middle percentiles seemed statistically insignificant. This finding is consistent with evidence from Chile and Colombia (Berdegue et al., 2015). However, the coefficients across the percentiles were rarely statistically different from each other (except for that of the 90th, which was statistically larger than we found for the 30th).

However, the size of the coefficients in Table 8 as well as the heterogeneity in impacts from our quintile regressions in Figure 2 deserve further scrutiny. The size of the coefficients in Table 8 are small, because, relative to the mean night-light intensity in our sample, increasing night-light intensity by one digital number involved the tripling of current average night-light intensities in our sample. Those in the lower and higher welfare percentiles were more likely to benefit from urban expansion than those in the middle welfare percentile, and this pattern drove potential heterogeneities in the impact of urban expansion and, consequently, of associated welfare inequalities. (See our quantile regressions in Figure 2.) This implies that potential welfare inequalities were mainly driven by those who benefited more than others and not by the fact that some groups were affected by urban expansion. This evidence may relieve concerns regarding potential adverse impacts of urban expansion, especially if projected over a longer term.

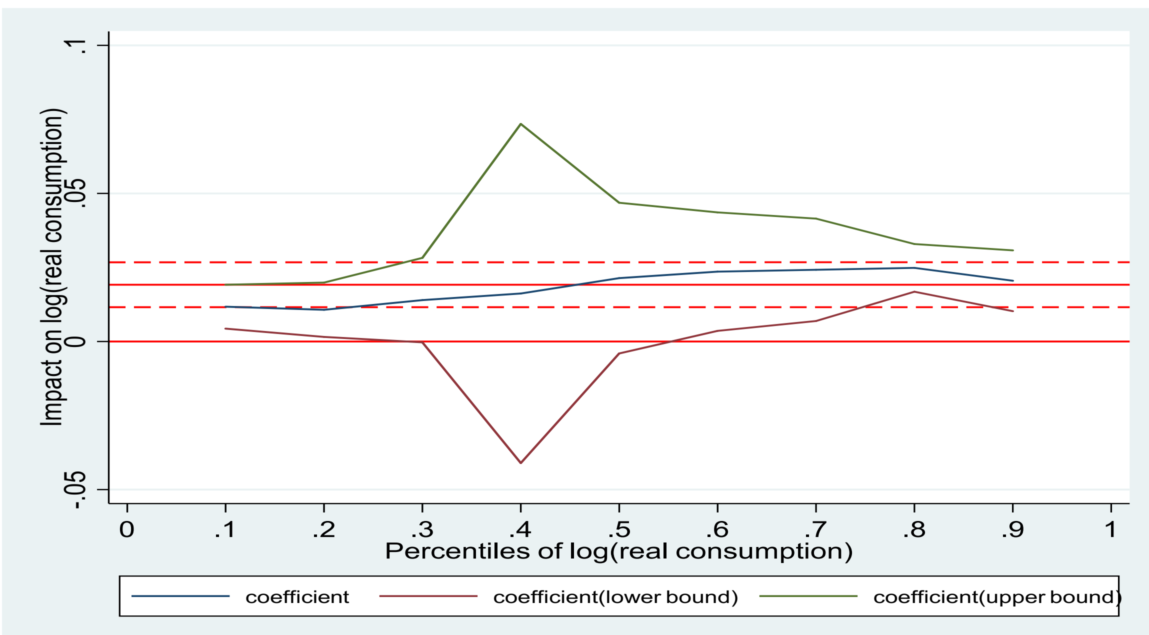
[18] These decomposition analyses were carried out through the Shapley decomposition approach and are available upon request to the authors.

Table 8: 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

Source: Authors' calculations based on data from the ESS 2011 and 2013 for rural and small towns.
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. *$p< 0.10$, **$p< 0.05$, ***$p< 0.01$.

Figure 2: Quantile Regressions Results on the Impact of Night-Light Intensity on Household Welfare



Source: Authors' calculations based on data from the ESS 2011 and 2013 for rural and small towns.
Notes: Estimates were run through the Stata command *qreg2*, developed by Parente and Santos Silva (2016), We augmented the main specification in Equation 1 by including the mean of the regressors. The unbroken horizontal red line represents the average effect (as reported in Table 4) while the two dashed horizontal red lines identify the confidence interval of the average effect. The specification used here is the same as that reported in Table 4, Column 3.

5.2 Robustness Exercises

In an attempt to probe the robustness of our main results, we conducted important empirical exercises to address two identification threats. First, despite the fact that households have limited control over urban growth, they might endogenously sort their residences through migration decisions. Households might migrate to areas that are urbanizing or to areas with higher labor-market potential. To explore whether such endogenous migration patterns had driven our main results, we restricted our sample to those households whose members had lived in the area for a long time. In particular, we excluded recent migrants, estimating similar regressions. Table 9 provides these estimates, which are similar to those based on full-sample estimates. This suggests that endogenous selection and migration of some households did not drive much of the effect.

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*** (0.005)	0.015*** (0.005)	0.019*** (0.007)
Household characteristics	Yes	Yes	Yes
Enumeration area FE	No	Yes	Yes
Household fixed effects	No	No	Yes
Year dummies	Yes	Yes	Yes
R-squared	0.19	0.41	0.73
No. Observations	5315	5315	5315

Source: Authors' calculations based on data from the ESS 2011 and 2013 for rural and small towns.
Notes: NTL stands for night-light intensity. In this table we employed mean night-light intensity across a buffer zone of 10km^2. Standard errors, clustered at the enumeration-area level, are given in parenthesis. $^{*}p<$ 0.10, $^{**}p<$ 0.05, $^{***}p<$ 0.01.

Our second robustness exercise explored the role of omitted variables in confounding causal impacts. Urbanization is a process that may correlate with other unobservable infrastructural and social developments. These omitted variables and trends may correlate with our measure of urbanization: night-light intensity. To judge the stability of our estimates to some potentially omitted variables, we employed an empirical technique developed by Oster

(2019) and estimated the lower and upper bounds of our estimates. Oster proposed 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 outcome variables. The estimates from uncontrolled and controlled regression specifications were very similar, suggesting that omitted variables, including those that could be controlled in our specifications, had few effects and little confounding role. In particular, the identified set of the urbanization coefficient excluded zero, which suggests that our estimates were robust against omitted-variable bias. This was not surprising given that we relied on temporal variations in night-light intensity, which could reasonably be argued to be exogenous to micro-level household decisions. All our main effects fell between these two bounds. This suggests that our results were 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's (2019) Approach

Outcome variable	(1) Uncontrolled (baseline) effects, [$\dot{R}$]	(2) Controlled Effects, [$\tilde{R}$]	(3) Identified Set
Log (real consumption)	0.016*** [0.002]	0.019*** [0.068]	[0.019, 0.022]
Labor supply (total working hours per adult)	0.292*** [0.001]	0.318*** [0.031]	[0.318,0.345]
Labor supply (working hours non-farm)	0.267*** [0.001]	0.284*** [0.034]	[0.284,0.302]
Labor supply (working hours wage-related)	0.288*** [0.001]	0.289*** [0.011]	[0.289, 0.294]

Source: Authors' calculations based on data from the ESS 2011 and 2013 for rural and small towns.
Notes: NTL stands for night-light intensity. Standard errors, clustered at the enumeration-area level, are given in parenthesis. *p< 0.10, **p< 0.05, ***p< 0.01. As in Oster (2019), in the estimations reported in Column 3, R_{max}=min(2* $\tilde{R}$, 1), δ=1. Results were qualitatively the same when a lower share of $\tilde{R}$ (i.e., <2) was used. Similarly, results remained consistent for the other extreme bound of δ (i.e., = -1). For Equation 2, we used the full set of controls reported in Table 4, Column 3.

VI. Conclusions

Despite evolving evidence that Africa is experiencing urbanization in a different way (e.g., Jedwab, 2012; Henderson, Roberts & Storeygard, 2013; Gollin, Jedwab & Vollrath, 2016), empirical evaluation of the welfare implications of urban-development programs in Africa remains scant. In particular, the welfare implications of the recent and remarkable growth of small towns 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 have been based on aggregate and census-based indicators, which cannot sufficiently capture significant heterogeneities and short-term dynamics in urban expansion or a continuum of rural-to-urban transformation at various stages and speeds.

In this paper we used objective markers of urbanization to explore the short-term implications of urbanization in rural areas and small towns in Ethiopia on household welfare and livelihood. Following recent successful attempts, we employed satellite-based night-light-intensity data to capture urban features and growth. For such a purpose, we linked household-level longitudinal data with satellite-based night-light intensity. In particular, we applied this new marker of urbanization to identify and quantify the welfare implications of recent urbanization trends in Ethiopia, which mostly involved the expansion of small towns. Studying urban-development programs in Ethiopia provides an interesting case for some important reasons. Initial levels of urbanization were low, though urban growth in Ethiopia remains above the sub-Saharan African average and regulating urban expansion is a top priority of the Ethiopian government. Indeed, Ethiopian government remains sufficiently vigilant and committed to managing and monitoring current and future urban expansion. Most of the policy discourse in this regard has not been informed by rigorous evaluations, however. In an attempt to inform these debates, we merged georeferenced longitudinal household data from the Living Standard Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) and satellite-based time series night-light-intensity data for Ethiopia. To estimate the causal effect of urbanization on household welfare, we exploited the longitudinal and spatial variations in our measure of urbanization and hence estimated household fixed effects models.

We found that urban growth, particularly the expansion of small towns, as measured by night-light intensity, was associated with improvement in household welfare. In particular, we found that a one unit (digital number) increase in night-light intensity was associated with about a 2% improvement in household welfare. This result was robust to alternative empirical specifications and sources of bias. Much of these improvements in household welfare appear to have been driven by the positive labor-market impacts of urban growth. More specifically, urbanization improved household engagement in non-farm (salaried) economic activities. We also found some positive impacts of urban growth on the price of food. The increase in consumer prices and the push to migrate, however, could only marginally explain the impact mechanism.

We also found suggestive evidence that urbanization was associated with welfare inequality. We showed that potential dynamics in urban expansion may have triggered welfare inequality among households living in a specific community. Relatedly, we also found significant heterogeneities in the impact of urban growth. Our quantile regressions showed that households at the lower and higher welfare percentiles were more likely to benefit from urban growth than those in the middle welfare percentile. Nevertheless, the size of effects on welfare inequality was marginal.

Our results have important implications for public-policy debates on the consequences and implications of urban expansion. Our findings highlight the fact that, on average, urban expansion can improve household welfare, particularly as it creates labor-market opportunities that can improve household income. Such improvements may not be uniformly distributed, however, as suggested by the heterogeneous impacts we documented and the slightly higher inequality associated with urban expansion. The latter result highlights the trade-off associated with urban expansion: an improvement in the average welfare of households and an increase in welfare inequality in a community. This trade-off reinforces the need to regulate and monitor urban expansion in Ethiopia in a way that can benefit larger groups.

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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)
Sex of head of household	0.021	-0.028	0.022	-0.026
	(0.021)	(0.097)	(0.021)	(0.097)
Ln(age of head of household)	-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 (borrowed from formal source)	-0.004	-0.068	-0.004	-0.069
	(0.028)	(0.042)	(0.028)	(0.042)
Enumeration area FE	Yes	--	Yes	--
Household 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 employed maximum and total night-light intensities across a buffer zone of 10km2. The first two columns use maximum night-light intensity while the last two columns use the sum of night-light intensities. Standard errors, clustered at the enumeration-area level, are given in parenthesis. *p< 0.10, **p< 0.05, ***p< 0.01.