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Can Urbanisation Improve Household Welfare? Evidence From Ethiopia

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Abstract

Despite evolving evidence that Africa is experiencing urbanisation in a different way, empirical evaluations of the welfare implications of urban-development programs in Africa remain scant. We investigate the welfare implications of recent urbanisation processes in Ethiopia using household-level longitudinal data and satellite-based nightlight intensity. We also examine the impact of urban growth on the composition of household consumption and welfare. We employ temporal and spatial variations in nightlight intensity to capture urban expansion and growth. Controlling for time-invariant unobserved heterogeneity across individuals and localities, we find that urbanisation, as measured by nightlight intensity, is associated with significant welfare improvement. We find that tripling existing average nightlight intensity in a village is associated with a 42–46% improvement in household welfare. Urbanisation is also associated with a significant increase in the share of non-food consumption, which is a good measure of overall welfare and poverty. In addition, we find significant heterogeneity in urban expansion across major towns and small towns. Urban expansion in rural areas and small towns appears more impactful than similar expansion in major cities. Finally, quantile regression results suggest that better-off households are likely to benefit more from urban expansion, which may translate into higher inequality across households or communities. Our results can inform public policy debates on the consequences and implications of urban expansion in Africa.

Keywords: sub-Saharan Africa, Ethiopia, labour-market outcomes, welfare, nightlight intensity, urbanisation

JEL classification: H53, O18, D63

1. Introduction

The world has experienced unprecedented levels of urbanisation[1] over the past five decades, with the highest urban growth rates occurring in developing countries. Africa is expected to be the fastest urbanising continent from 2020 to 2050 (United Nations, 2014). Urbanisation involves major structural, socioeconomic and land-use transformations. Most urbanisation processes involve large public and private investments and are generally considered the engine of high economic growth. These processes and developments may take place differently across contexts and continents, however. For instance, many argue that Africa's urbanisation trend remains distinct (Jedwab, 2012; Henderson *et al*., 2013) and that Africa is urbanising without structural transformation and industrialisation (Fay and Opal, 2000; Jedwab, 2012; Jedwab and Vollrath, 2015; Gollin *et al*., 2016).[2] The pace of urbanisation in many African countries has surpassed the levels of structural and political transformations 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 urbanisation trends present new opportunities and challenges for ensuring sustainable and inclusive economic growth in Africa. Previous literature on urbanisation has mostly focused on large cities and metropolitan areas. However, much of the urbanisation trends in most African countries involve expansion and growth of secondary towns (e.g., Ingelaere *et al*., 2018; Christiaensen *et al*., 2019a; Christiaensen *et al*., 2019b; Christiaensen and Kanbur, 2017). 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). Poverty is becoming an urban phenomenon (Ravallion *et al*., 2007; Dorosh and Thurlow, 2014), and economic inequality has been growing in African urban centers (World Bank, 2013). The urbanisation of poverty is usually argued to be driven by migration of the rural poor to urban areas (e.g., Ravallion *et al*., 2007; Elhadary and Samat, 2012) and the vulnerability of urban residents to climate shocks (Cohen and Garrett, 2010). In addition, urbanisation 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] Furthermore, urbanisation is commonly associated with an increase in income inequality, particularly at the early stages of development (Kuznets, 1955; Kanbur and Zhuang, 2013). This is believed to be the case when investments in infrastructure and institutions are limited, a common pattern in many developing countries where urban expansion has occurred (Black and Henderson, 1999). Recent urbanisation trends in sub-Saharan Africa (SSA) are not accompanied by adequate investments and thus did not result in the required levels of industrialisation (Jedwab, 2012; Henderson *et al*., 2013; Gollin *et al*., 2016).

1 The terms 'urbanization', 'urban growth' and 'urban expansion' are synonymously used in the text. By these terms we mean to identify the expansion of local economic activity and infrastructure.

2 Urbanization in Africa is commonly linked to creation of 'consumer cities' rather than 'producer cities' that depend upon manufacturing sectors (Jedwab, 2013; Gollin *et al*., 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).

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

On the other hand, some empirical studies highlight the positive effects of urban expansion, including long-term welfare implications (World Bank, 2009; Glaeser, 2011). Urbanisation involves shifting employment opportunities from agriculture to more remunerative and productive industrial and non-farm employment (Bloom *et al*., 2008; Diao *et al*., 2019). Other studies have shown that urbanisation improves market linkages by increasing demand for high-value agricultural products and non-farm employment (Cali and Menon, 2012; Arouri *et al*., 2016; Datt *et al*., 2016; Swain and Teufel, 2017; Vandercasteelen *et al*., 2018).

Urbanisation has also been found to improve access to markets and thus may generate higher income to support rural livelihoods (Cali and Menon, 2012). Consistent with this channel, several studies have indicated that urbanisation rates are positively associated with higher per-capita income (Dorosh and Thurlow, 2014; Ravallion *et al*., 2007; Bloom *et al*., 2008) and a more diversified income portfolio (Mezgebo and Porter, 2020). Urbanisation may also influence the welfare of rural households by enhancing investments in farming technologies and by creating market opportunities for agricultural products (Swain and Teufel, 2017). Urban expansion may encourage rural households to tailor their agricultural production in response to urban growth (Stage *et al*., 2010; Vandercasteelen *et al*., 2018). Relatedly, a key feature of the urbanisation process concerns the movement of people from remote and rural areas to urban areas, a trend that may affect the labour-market outcomes of urban and rural dwellers (e.g., Henderson *et al*., 2017).

The findings reported above may not necessarily apply to all forms of urbanisation. For example, some form of urbanisation processes may entail the creation of major towns, while most urbanisation processes in sub-Saharan Africa entail continuum rural–urban transformations at different stages. Furthermore, some stages and types of urbanisation may be more impactful and welfare-improving than others. For example, recent studies show that secondary towns may contribute to poverty reduction and welfare improvements to a larger extent than do bigger cities (e.g., Dorosh and Thurlow, 2013, 2014; Datt *et al*., 2016; Christiaensen and Kanbur, 2017). The growth of small towns can create non-farm employment and increase income opportunities for youth (de Brauw and Mueller, 2012). This may also shift the primary source of income and employment of rural households located near small towns (Diao *et al*., 2019). Nevertheless, despite evolving evidence that Africa is urbanising differently, empirical evaluations of the welfare implications of urban-development programs in Africa remain scarce. In particular, the implications of urbanisation on households' welfare dynamics have not been well-explored. Additionally, as the short review above indicates, urbanisation can positively or negatively affect various welfare dimensions. Hence, its net welfare effect depends on which positive or negative impacts prevail.

The scarcity of empirical studies on the implications of urbanisation on household welfare can partly be attributed to the lack of an objective measure of the level and dynamics of urbanisation. Previous attempts to measure urbanisation and urban growth use census-based dichotomous rural–urban indicators that cannot capture: (i) potential heterogeneities among urban areas, (ii) rapid temporal dynamics of urbanisation and (iii) potentially complex and nonlinear relationships between urbanisation and household livelihoods (Champion and Hugo, 2004; Dahly and Adair, 2007; Amare *et al*., 2020). As opposed to a binary phenomenon, urbanisation often involves a continuum of rural–urban transformations at various stages, which census-based indicators are less likely to capture.[5] Thus, alternative and reliable metrics of urbanisation are crucial for understanding the implications of urbanisation and hence for informing urban development policies in Africa.

The advent of satellite-based nightlight data offers an interesting opportunity to measure urbanisation and urban expansion. Given that night light remains a fundamental urban amenity, nightlight intensity is a plausible marker of urbanisation and urban growth (e.g., Elvidge *et al*., 1997; Imhoff *et al*., 1997; Sutton, 1997; Elvidge *et al*., 2021). This is particularly appealing for developing countries where measures and statistical indicators of urbanisation are neither readily available nor standardised. Recent studies have successfully applied nightlight-intensity data to study the implications of urbanisation in Africa (Michalopoulos and Papaioannou, 2013; Storeygard, 2016; Abay and Amare, 2018; Amare *et al*., 2020).

In this paper, in line with the current literature (e.g., Gibson *et al*., 2021), we employ satellite-based nightlight intensity data as a marker of the expansion of local economic activity and infrastructure to study the short-term implications of urbanisation on household welfare in Ethiopia. We are particularly interested in identifying whether recent urbanisation trends in Ethiopia are improving household welfare. Urban development programs in Ethiopia share most of the challenges that other African urban centers currently face.[6] Cognizant of this, the Ethiopian government has recently given particular attention to urbanisation trends in the growth and transformation strategy document (Federal Democratic Republic of Ethiopia, 2016). Indeed, monitoring and regulating trends in urban expansion have been incorporated into the Ethiopian government's Growth and Transformation Plan (GTP-II) to ensure inclusive and sustainable growth. However, despite some attempts, the welfare implications of recent trends in urban expansions in Ethiopia remain unexplored.[7]

We assemble georeferenced and household-level longitudinal data from three rounds (2012, 2014 and 2016) of Ethiopia's Living Standard Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA). The LSMS-ISA household surveys followed the same households across time, providing longitudinal variation in our measure of urban expansion and household welfare. We merged the household survey data with village-level nightlight intensity time-series data from the Visible Infrared Imaging Radiometer Suite (VIIRS) satellite imageries. By exploiting exogenous spatial and temporal (i.e., across and within EA) variations in the urban expansion (nightlight intensity) and controlling for unobserved individual and community heterogeneity, we examine the welfare implications of potential dynamics in urbanisation. We also investigate whether urban expansion affects the composition of household welfare. Finally, we examine potential heterogenous implications of urban expansion across large towns and small towns as well as across welfare percentiles.[8]

We find that urban expansion, as measured by nightlight intensity, has a positive *short-term* effect on household welfare. We find that tripling the existing average nightlight

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 Despite from a low base, with urban population of about 20% in 2020, annual urban growth in Ethiopia amounts to about 4.5%, which is higher than the sub-Saharan African average (World Bank, 2011).

7 Indeed, some anecdotal evidence shows that trends in urban expansion in Ethiopia may not benefit all groups equally (e.g., Broussard and Teklesellasie, 2012; Mezgebo, 2017).

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

intensity in a village is associated with a 42–46% improvement in household welfare. Urbanisation is also associated with a significant change in the composition of household consumption by disproportionally increasing non-food consumption in the overall welfare. This is consistent with the prediction of the first Engel's law: if urbanisation increases overall welfare, then this is expected to reduce the share of food consumption in overall welfare. We also find important heterogeneities in the impact of urban expansion in major towns and small towns as well as across the distribution of household welfare. Although rural areas and small towns in Ethiopia appear to be experiencing welfare decline, urban expansion in rural areas and small towns are more impactful in terms of improving household welfare. Our findings are consistent with evolving literature examining the welfare effects of the expansion of secondary towns (Christiaensen *et al*., 2013; Christiaensen and Kanbur, 2017; Gibson *et al*., 2017). Our quantile regressions suggest that households in higher consumption percentiles enjoy slightly higher welfare gains from urban growth. This may insinuate that urban expansion may slightly trigger welfare inequality among households and communities.

Our results can inform public policy on the consequences and implications of urban expansion in Africa. However, it is worth noting that urbanisation may involve other structural transitions that complicate identifying potential channels through which urbanisation can affect household welfare. In addition, as we discuss below, the type of urbanisation processes we studied may be different from the typical urbanisation that involves the creation of major cities and metropolitan areas. Therefore, the results and policy implications we generate in this study may not apply to every urbanisation process.

The remaining sections of the paper are organised as follows. Section 2 describes the data, the definition of the key variables and presents some descriptive statistics. Section 3 presents the empirical strategy to identify the effect of urbanisation on household welfare and the composition of household consumption. Sections 4, 5 and 6 discuss the empirical results, heterogeneous impacts and some robustness checks, respectively. Finally, in Section 7, we provide concluding remarks.

2. Data and measurement of key variables

2.1. Data and descriptive statistics

We employ two different data sources: the LSMS-ISA for Ethiopia[9] and nightlight intensity data from NASA/NOAA VIIRS satellite imageries hosted at the Colorado School of Mines' Earth Observation Group.[10] The LSMS-ISA, also known as the Ethiopia Socioeconomic Survey (ESS), are longitudinal household datasets collected every two years and cover a wide range of topics, including the consumption of rural and urban households. More importantly, the ESS data provide georeferenced enumeration areas (EAs), which enable us to pinpoint the location of EAs and merge them with nightlight-intensity data that are gathered from satellites.[11]

9 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.

10 The VIIRS imageries can be downloaded from https://eogdata.mines.edu/products/vnl/.

11 In the context of Ethiopia, an enumeration area covers about 150–200 households in rural areas and 150–200 housing units in urban areas.

Table 1: Summary Statistics of Sample Households

Household and community characteristics	2011/12 round		2013/14 round		2015/16 round	
	Mean	SD	Mean	SD	Mean	SD
Head of household is a male	0.79	0.41	0.76	0.43	0.76	0.43
Age of head of household	44.33	15.50	44.59	15.73	46.67	15.26
Head of household attended school (0/1)	0.38	0.48	0.46	0.50	0.46	0.50
Household size	5.07	2.26	5.29	2.48	5.85	2.57
Household size in adult equivalence	4.09	1.86	3.87	1.89	3.97	1.88
Average age of household	26.57	10.92	24.26	11.16	26.09	12.58
Farm size (ha)	1.30	3.32	1.45	8.60	2.43	54.27
Livestock (TLU)	3.93	4.74	3.70	4.95	3.88	5.02
Urban dummy (0/1)	0.06	0.24	0.25	0.43	0.27	0.44
Household has non-farm income	0.21	0.40	0.26	0.44	0.25	0.43
Access to microfinance	0.30	0.46	0.31	0.46	0.35	0.48
Access to formal credit	0.10	0.30	0.11	0.32	0.09	0.28
No. observations	3,324		4,243		3,869	

Source: Authors' calculations based on data from the ESS 2011/12, 2013/14 and 2015/16. Summary statistics are weighted using sampling weights.

We use three waves of the ESS data for Ethiopia: the first was conducted in 2011/12, the second and third rounds were conducted in 2013/4 and 2015/16, respectively. The consumption modules were administered in the early months of 2012, 2014 and 2016. The first wave, which covered only rural areas and small towns, interviewed a random sample of households from 333 EAs throughout all Ethiopian regions. The second round re-interviewed the same households from the first round as well as additional random sample of households from major towns and cities, increasing the sample to cover 433 EAs.[12] The third round re-interviewed those from the second round. Thus, the first round was representative of rural and small towns of Ethiopia, while the second and third rounds were representative of the whole country. Table 1 provides descriptive statistics of household and community-level characteristics. We mainly report the basic demographic and socioeconomic characteristics of households, which are expected to influence consumption and production decisions. We disaggregate and present these descriptive figures across survey rounds. The summary statistics given in Table 1 remain comparable across rounds. Those variables showing important differences across rounds are related to the sample composition across waves. For instance, the first round covers only rural areas and small towns, and because of this, the share of households living in urban areas is much smaller in the first round.

12 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.

2.2. Defining and describing welfare and related outcomes

We use real consumption spending as a proxy for household welfare. Consumption spending included all home-produced and purchased food items consumed by the household.[13] Our consumption measure includes spending on food and non-food items. 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, and medium and large towns (as defined by the census-based rural–urban indicator of the CSA). As shown in Panel A of Table 2, households' real consumption spending decreased over the years. This is mainly because of the large increase in prices (CPI) in the later rounds, despite some increase in nominal consumption.[14] However, such a decline in household welfare is more pronounced for rural areas and small towns, while households living in medium and large towns enjoy a modest improvement in welfare (at least in the last two rounds). This implies that there is significant spatial variation in the welfare dynamics in Ethiopia, which deserves policy attention and further research. This is consistent with other recent studies that have investigated the welfare dynamics of Ethiopian households using similar data (e.g., Fuje, 2018, Jolliffe *et al*., 2016; Nakamura *et al*., 2020).[15] As expected, consumption remained higher in households located in medium and large towns, compared to those located in rural areas and small towns. This is not surprising given that households in urban centers have better incomes and access to services such as power, communication, schools and sanitation services.

Besides examining the potential dynamics in overall consumption, we also assess changes in its composition. This is important to understand the overall and relative impact of urban expansion on various components and aspects of welfare and the potential contribution of the urbanisation process to the structural transformation. If urbanisation increases households' income, then, in accordance with the Engel curve, we expect that urbanisation also increases the share of non-food commodities. Before formally testing the impact of urban growth on the share of non-food consumption, we assess whether the Engel curve's prediction and hence positive association between total welfare and share of non-consumption hold. As expected, conditional on year fixed effects, we find that higher welfare is significantly associated with a higher share of non-food consumption (the results are reported in Appendix

13 Local prices were applied to value consumption of home-produced foods.

14 For example, the overall CPI for December 2013 amounted to 123.8 with respect to 2011.

15 We are aware that these patterns differ from those based on the Household Consumption Expenditure Survey (HCES) (see World Bank, 2020). Potential explanations for such a difference are: first, the HCES collected consumption module over the year, while the ESS data collection for the consumption module was done between February and April. Second, the consumption module for the HCES included more items than that of the ESS.

Table 2: Summary of Consumption and Related Welfare Indicators

	2011/12	2013/14	2015/16
Panel A: full sample			
Nominal annual consumption per adult equivalence (ETB)	4941.58	5906.79	6777.35
Real annual consumption per adult equivalence (ETB)	5148.13	4861.34	4699.36
Food consumption per adult equivalence (ETB)	4219.16	3566.56	3475.13
Non-food consumption (ETB)	928.97	1294.78	1224.23
Share of non-food consumption over total consumption	0.19	0.25	0.25
Number of observations	3,324	4,243	3,869
Panel B: rural areas and small towns			
Nominal annual consumption per adult equivalence (ETB)	4941.58	5236.73	5718.33
Real annual consumption per adult equivalence (ETB)	5148.13	4378.70	4052.27
Food consumption per adult equivalence (ETB)	4219.16	3399.39	3161.84
Non-food consumption (ETB)	928.97	979.31	890.43
Share of non-food consumption over total consumption	0.19	0.22	0.22
Number of observations	3,324	3,131	2,941
Panel C: medium and large towns			
Nominal annual consumption per adult equivalence (ETB)		8849.72	11007.71
Real annual consumption per adult equivalence (ETB)		6981.13	7284.24
Food consumption per adult equivalence (ETB)		4300.77	4726.60
Non-food consumption (ETB)		2680.36	2557.64
Share of non-food consumption over total consumption		0.38	0.35
Number of observations		1,112	928

Source: Authors' calculations based on data from the ESS 2011/12, 2013/14 and 2015/16. *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. All values are weighted by population sampling weights in our data.

Table A1). The non-food consumption in our data includes spending on: education, batteries, kerosene, firewood, charcoal, candles, cigarettes and tobacco, hand soap, laundry soap, other personal care goods, transport and other related services.

2.3. Defining and measuring urbanisation and urban expansion

Despite the unprecedented levels of rural-to-urban transformations in developing countries in the last few decades, researchers and urban planners are still seeking more accurate measures of the level and dynamics of urbanisation. Most measures of urban expansion come from population censuses which are usually based on binary rural–urban indicators and are, therefore, inadequate to capture the rapid dynamics of urban expansion. Most of these indicators are aggregated at higher levels and are inhibiting the analysis of urbanisation impacts on households' livelihood. Because most censuses are conducted decennially in many countries, this measurement problem is not unique to developing countries.[16]

These measurement challenges have encouraged researchers and urban planners to look for alternative measures or markers of urbanisation. More recently, efforts have focused on constructing continuous and disaggregated indicators that can capture micro-level variations

16 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).

in urban expansion. For this purpose, satellite-based nightlight intensity data have attracted a great deal of attention because of their potential to capture the dynamics of urbanisation and related economic activities. Because access to electricity and lights remain key urban amenities, urban areas are expected to have higher nightlight intensities than rural areas. Based on this notion, satellite-based nightlight intensity has been commonly used as a marker of urbanisation (Elvidge *et al*., 1997; Imhoff *et al*., 1997; Henderson *et al*., 2003; Sutton *et al*., 2010; Storeygard, 2016; Abay and Amare, 2018; Amare *et al*., 2020).

Following this trend, we measure urbanisation and urban growth by using nightlight intensity from satellite imageries. These imageries provide a continuous measure of the temporal dynamics of the urbanisation process. The Satellite-based luminosity data we employ in this study come from the VIIRS sensors aboard NASA/NOAA JPSS satellite. The VIIRS collects infrared DNB from every location on the planet at about a 15 arc-second or 742-meter resolution. These imageries are further processed for public use by the EOG at the Colorado School of Mines. As mentioned above, the luminosity data measure and express light intensity in radiance units, i.e., nanowatts, for each pixel that covers 742 meters (one side of the square) resolution on the ground.

We employed Version 2 annual composite of the VIIRS-DNB time series, which runs from 2012 to the present. To calculate the nighttime radiance values for the areas in our study, we construct a 10 km radius buffer zone around ESS enumeration areas. We then extracted the mean and total radiance values for these buffer zones. Unlike the DMSP-OLS imageries, which have several limitations, including saturation of the DN numbers at 63, the VIIRS-DNB imageries are available at a higher resolution and hence appropriate to measure urbanisation processes at a much finer detail (see Donaldson and Storeygard, 2016; Michalopoulos and Papaioannou, 2018; Elvidge *et al*., 2021; Li *et al*., 2020). The DMSP-OLS was also discontinued in 2013, and hence, imageries corresponding to the latest LSMS-ISA surveys in 2015/16 are not available. Moreover, the VIIRS is well-calibrated both onboard the satellites and by the EOG using the latest algorithms for light noises caused by other human activities (e.g., gas fares and forest fires), and proved to outperform imageries from the DMSP-OLS (Elvidge *et al*., 2009; Elvidge *et al*., 2021). Also, as discussed by Gibson *et al*. (2021), the DMSP-OLS imageries are particularly unsuccessful in measuring urbanisation outside the cities (where the output density is low) and its interspatial heterogeneity. Since the main interest of this paper is to understand how the urbanisation process affects welfare dynamics nationally, including rural areas and small owns, as well as whether such a relationship has followed heterogenous patterns across regions, then the DMSP-OLS imageries are not suitable. Hence, we use the VIIRS-DNB, which has improved features that are helpful to measuring urbanisation. Most importantly, the longitudinal nature of these data and their availability at high spatial resolution allow us to trace the dynamics of urbanisation at a micro-level.

Considering the context in Ethiopia, our luminosity data were highly skewed to the left, mainly because many parts of the developing world remain dark (Michalopoulos and Papaioannou, 2018). For instance, at the aggregate level, the average nighttime light radiance values for Kenya, which has the highest level of luminosity in the East African region, were 0.019 and 0.038 for 2012 and 2016, respectively. The aggregate mean radiance values for Ethiopia during the same period were 0.008 and 0.011. To provide a perspective, these are low nighttime light radiance compared to some advanced countries such as South Korea, which has 327 times brighter nighttime lights than Ethiopia in 2016. In terms of changes

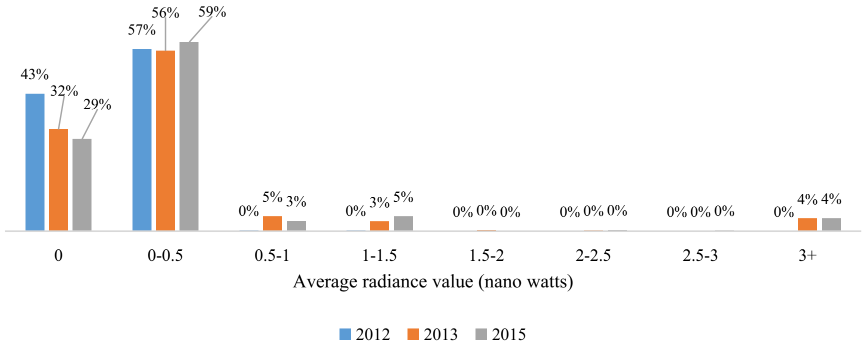

Figure 1: Distribution of Nighttime Light Intensity Across Years. *Source*: Authors' calculations based on VIIRS-DNB data. *Notes*: Average radiance value in nanoWatts/cm2/sr.

over time, nighttime light radiance for Ethiopia has been growing by 8.4% annually during 2012–2016, which is still higher compared to growth in Kenya. This is the case in our context because our household-level data covered a large part of rural Ethiopia, where towns are relatively small and often have limited access to electricity resulting in a low level of detectable lights at night (see Figure 1). For instance, in 2012, about 42% of the EAs have no detectable lights, although it improved over time with only 32%, and 29% of the EAs in 2014 and 2016 having no detectable nighttime lights. However, it should be noted that the large drop in the percentage of EAs with no detectable lights between 2012 and 2014 could be due to the inclusion of more medium and large towns in the 2014 and 2016 waves. Regardless, even though highly skewed, the nightlight data provide more variation and dynamics than the commonly used census-based rural–urban indicator.

We merged the longitudinal ESS with the EA level annual composite of VIIRS nighttime radiance data.[17] Table 3 provides summary statistics of the radiance values as a measure of urbanisation for the full sample (panel A), rural areas and small towns (panel B) and medium and large towns (panel C). The average, maximum and total radiance value within the 10 km radius buffer zone increases over time for all groups: the full sample, rural areas and small towns and medium and large towns. As expected, the radiance values are generally smaller for rural and small towns (panel B) compared to medium and large towns in all waves. For the full sample, the average radiance value increased from 0.02 in 2012 to 0.36 in 2016 (but this is mostly because of the inclusion of medium and large towns in the later rounds) and from 0.23 to 0.31 between 2014 and 2016.[18] Panels B and C suggest that both rural areas (and small towns) and medium and large towns have experienced some increase in night light

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

18 While the LSMS-ISA consumption data for the first round was collected between January and March for the first wave, data were collected in February–April for the latter two waves in 2014 and 2016. Since the VIIRS night-time radiance data starts in April 2012, the annual composite image for 2012 is not full year observation. Rather an average of April–December months only. However, for all other years (2013/14 and 2015/16 waves, in our case), the annual composite imageries processed by EOG takes into account all 12 months of the respective years.

Table 3: Summary Statistics of Key Policy Variables

	2011/12	2013/14	2015/16
Panel A: full sample			
Mean nightlight intensity (nanoWatts/cm2/sr)	0.02	0.24	0.31
Maximum nightlight intensity (nanoWatts/cm2/sr)	1.62	3.90	4.87
Total (sum) of nightlight intensity (nanoWatts/cm2/sr)	34.28	351.36	463.83
Number of observations	3,324	4243	3,869
Panel B: rural areas and small towns			
Mean nightlight intensity (nanoWatts/cm2/sr)	0.02	0.03	0.03
Maximum nightlight intensity (nanoWatts/cm2/sr)	1.62	1.66	2.12
Total (sum) of nightlight intensity (nanoWatts/cm2/sr)	34.28	39.40	49.61
Number of observations	3,324	3,131	2,941
Panel C: medium and large towns			
Mean nightlight intensity (nanoWatts/cm2/sr)		1.15	1.42
Maximum nightlight intensity (nanoWatts/cm2/sr)		13.77	15.83
Total (sum) of nightlight intensity (nanoWatts/cm2/sr)		1721.52	2118.48
Number of observations		1,112	928

Source: Authors' calculations based on Version 2 annual composite VIIRS-DNB imageries processed by EOG at the Colorado School of Mines.

Notes: Nightlight intensity or DNB are in radiance values, i.e., nanoWatts/cm2/sr. Summary statistics are weighted using sampling weights.

intensity. Similarly, the average values of the sum of NTL within an EA and of the maximum NTL intensity steadily increased for both rural and small towns and medium and large towns, corroborating the urbanisation trend observed across the country. For example, between 2014 and 2016, the total NTL intensity grew by 26% in rural areas/small towns and by 23% in medium/large towns. As shown in Figure 1, part of the increase in the level of radiance can be attributed to more rural and small towns following the gradual increase in rural electrification. It is also suggestive of the emergence of small urban corridors as opposed to the intensification of a few cities. This is not surprising given the Ethiopian government's recent investments in infrastructure. However, given the level of increase in nightlight intensity in Table 3, the type of urbanisation we are reporting here mostly represents the expansion of secondary towns, which is slightly different from the typical large-scale creation of large cities and metropolitan areas studied in the urbanisation literature. We explored whether these dynamics in these indicators of urbanisation could predict and cause potential welfare improvements. Given the temporal gap every round (two years) and the overall duration (four years) we are covering in this study, the impact we can detect is likely to be a short-term welfare effect.

3. Empirical strategy

Quantifying the impact of urbanisation poses several empirical challenges, including endogeneity arising from omitted attributes and measurement problems. This is partly because most urbanisation programs are accompanied by economic growth that can influence overall livelihood. In light of this, we employ a household level panel dataset and alternative econometric approaches that exploit temporal (within the household) and spatial variations in nightlight intensity while also controlling for time-invariant heterogeneities across households and EAs.

Because we conduct our analysis at the household level, potential dynamics in urbanisation could be exogenous to short-term livelihood and welfare outcomes. Hence, we exploit the longitudinal variations in our measure of urbanisation by estimating household-fixed-effects models. In an alternative and less demanding specification, we control for EA fixed effects. These fixed effects models difference out time-invariant factors across villages and households. These fixed effects specifications are relatively conservative approaches because they require reasonable variations in our measure of urbanisation across time. We employed real consumption per adult equivalence as our direct measure of welfare. Thus, our estimable welfare function is as specified below:

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

where $\ln C_{hvt}$ is the logarithmic value of real consumption per adult equivalence for household h residing in an enumeration area v and period t. U_{vt} stands for the level of urbanisation for each enumeration area (village) and time, which is measured using average or total nightlight intensity in each EA. H_{hvt} captures additional household-and village-level time-varying characteristics, δ_h and δ_t represent household-and time-fixed effects, respectively. In the absence of time-varying unobservable factors that affect both consumption and urbanisation, 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, we believe that β_1 captures the causal relationship between urban growth and welfare dynamics. In particular, given that households had little influence on urban expansion, we argue that the empirical specification in equation (1) can reasonably identify the impact of urbanisation 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 minimise such contemporaneous shocks to our outcomes and the explanatory variables, we control for additional community-level factors.

Besides the level of overall welfare, we also examine whether urban expansion affects the structure of household consumption. According to Engel's prediction, we expect that, if urban growth increases welfare, the share of non-food consumption increases with urbanisation. To probe this, we estimate the following equation characterising the share of non-food consumption in overall welfare:

$$Share_{hvt} = \alpha_1 U_{vt} + \alpha_2 H_{hvt} + \delta_h + \delta_t + \epsilon_{hvt} \quad (2)$$

Where all terms except $Share_{hvt}$ are as defined as in equation (1). $Share_{hvt}$stands for the share of non-food consumption in overall welfare. If urbanisation improves household income and livelihoods, we expect α_1 to be statistically significant and assume a positive value.

We also explore potential heterogenous impacts of urban growth on various types of households. As shown in section 2, both small towns/rural areas and medium/large towns show some increase in nightlights intensity over the periods 2012–2016. However, over the same period, welfare in small towns/rural areas decreased while it modestly increased in medium and large towns. If, as expected, urbanisation generates diminishing returns on welfare, the welfare effect of potential increase in nightlights can be larger in rural areas/small towns than in medium/large towns. We also investigate the impact of urbanisation on welfare distribution. To this end, we estimate quantile fixed-effects regressions to identify the type of households enjoying higher (lower) benefits associated with urban expansion.

Our key variables of interest vary at the village (enumeration area) level, implying that households living in the same enumeration area may share some unobserved effects, which can generate correlation in error terms. Thus, in all specifications, we cluster standard errors at EA (village) level. However, one may argue that, although households have limited control over urbanisation, their members might migrate to areas in which greater urbanisation is taking place or is expected to happen soon. To circumvent this, we run the same specification by dropping those households who recently migrated to the village they are living in during the survey period. This exercise serves to rule out potential biases due to endogenous migration decisions.

4. Estimation results: main specification

4.1. Urbanisation and overall household welfare

Before presenting our main results, the following clarifications are in order. Our primary outcome variable is expressed as the logarithmic transformation of real consumption per adult equivalence. Our secondary outcome of interest is the share of non-food consumption in overall consumption that captures the structure of household consumption. Our proxy for urbanisation is nightlight intensity, measured as mean and total intensity within an EA. Nightlight intensity is measured and expressed in radiance value in nanowatts/m^2/sr. We constructed average and total radiance values associated with each enumeration area.

Table 4 provides estimates based on the average nightlight intensity associated with specific enumeration areas. The first two columns provide unconditional relationships between longitudinal variation in nightlight intensity and household welfare. The first column shows results controlling for EA fixed effects, while the second column provides corresponding results controlling 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 exploit longitudinal variations in urbanisation to identify the impact of urban growth on welfare. We can clearly observe that higher nightlight intensity (urban growth) is positively associated with household welfare (consumption per per-adult-equivalence). More specifically, increasing the average nightlight intensity by one radiance (which requires tripling the most recent nightlight intensity in Table 3) is associated with about a 42–46% increase in household consumption. As shown in the last two columns, the effects remain robust even after controlling for important time-varying covariates. Given the low level of nightlight intensity in our sample, the size of the effect is plausible, mainly because increasing average nightlight intensity by one radiance entails tripling the recent level of nightlight intensity, which requires large public investments.

In Table 5, we provide slightly different estimates based on the total nightlight intensity associated with specific enumeration areas. We follow similar specifications as in Table 4,

Table 4: Nightlight Intensity and Household Welfare

Explanatory variables	(1) Log (real consumption)	(2) Log (real consumption)	(3) Log (real consumption)	(4) Log (real consumption)
NTL (mean)	0.4284***	0.4802**	0.4204***	0.4548**
	(0.1619)	(0.2314)	(0.1381)	(0.2023)
Sex of head of household			0.0028	−0.0211
			(0.0209)	(0.0952)
Ln (age of head of household)			−0.2574***	0.0351
			(0.0351)	(0.1377)
Education head (dummy)			0.1107***	0.0099
			(0.0205)	(0.0516)
Household size			−0.0512***	−0.0434***
			(0.0051)	(0.0159)
Ln (average age in household)			0.2618***	0.3332***
			(0.0341)	(0.0744)
Farm size (ha)			0.0002**	0.0001
			(0.0001)	(0.0001)
Urban (dummy)			0.0000	0.0000
			(0.0000)	(0.0000)
Ln (TLU)			0.1218***	0.0551**
			(0.0132)	(0.0232)
Non-farm income (dummy)			0.0190	0.0510
			(0.0208)	(0.0397)
Access to micro finance			0.0287	0.0265
			(0.0414)	(0.0523)
Access to formal credit (borrowed from formal source)			0.0357	0.0026
			(0.0312)	(0.0456)
Enumeration area FE	Yes	—	Yes	—
Household fixed effects	No	Yes	No	Yes
Year dummies	Yes	Yes	Yes	Yes
R-squared	0.3477	0.6871	0.4111	0.6959
No. observations	11,436	11,436	11,436	11,436

Source: Authors' calculations based on data from the ESS 2011/12, 2013/14 and 2015/16.

Notes: NTL stands for nightlight intensity. In this table, we employed mean radiance within a buffer zone of 10 km radius in each EA. Estimates were adjusted for sampling weights. Standard errors, clustered at the enumeration-area level, are given in parenthesis. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

controlling both for enumeration area and household fixed effects. These results confirm those in Table 4, implying that the total radiance around a specific location was associated with higher household welfare. For example, a one radiance increase in total nightlight in an EA is associated with a 0.03% increase in household consumption. These results remain comparable and robust across all specifications.

Besides highlighting the welfare implications of urbanisation, the results in Tables 4 and 5 reinforce the potential of nightlight intensity to detect short-term urban growth and associated trends. This is unlike the conventional census-based urbanisation indicators. In all our estimations, we included census-based measures of urbanisation as an indicator variable for urban areas. Despite capturing significant spatial variations in consumption

Table 5: Nightlight Intensity (Sum) and Household Welfare

Explanatory variables	(1) Log (real consumption)	(2) Log (real consumption)	(3) Log (real consumption)	(4) Log (real consumption)
NTL (sum)	0.0003***	0.0003**	0.0003***	0.0003**
	(0.0001)	(0.0002)	(0.0001)	(0.0001)
Sex of head of household			0.0028	−0.0211
			(0.0209)	(0.0952)
Ln(age of head of household)			−0.2574***	0.0351
			(0.0351)	(0.1377)
Education head (dummy)			0.1107***	0.0099
			(0.0205)	(0.0516)
Household size			−0.0512***	−0.0434***
			(0.0051)	(0.0159)
Ln (average age in household)			0.2618***	0.3332***
			(0.0341)	(0.0745)
Farm size (ha)			0.0002**	0.0001
			(0.0001)	(0.0001)
Urban (dummy)			0.0000	0.0000
			(0.0000)	(0.0000)
Ln (TLU)			0.1218***	0.0551**
			(0.0132)	(0.0232)
Non-farm income (dummy)			0.0190	0.0510
			(0.0208)	(0.0397)
Access to micro finance			0.0287	0.0265
			(0.0413)	(0.0522)
Access to formal credit (borrowed from formal source)			0.0355	0.0026
			(0.0312)	(0.0456)
Enumeration area FE	Yes	—	Yes	—
Household fixed effects	No	Yes	No	Yes
Year dummies	Yes	Yes	Yes	Yes
R-squared	0.3477	0.6871	0.4111	0.6959
No. observations	11,436	11,436	11,436	11,436

Source: Authors' calculations based on data from the ESS 2011/12, 2013/14 and 2015/16.

Notes: NTL stands for nightlight intensity. In this table, we employed total (sum) radiance within a buffer zone of 10 km radius in each EA. Estimates were adjusted for sampling weights. Standard errors, clustered at the enumeration-area level, are given in parenthesis. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

among households, this indicator showed no temporal dynamics and hence vanished in our fixed-effects estimations. This was expected as the last census was done in 2007. This implies that our measure of urbanisation using nightlight intensity better captures the short-term effects of urbanisation and associated trends, which otherwise could not be captured by the conventional census-based indicators of urbanisation. 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 (Column 3 of Table 4), larger household size is associated with lower welfare. In addition, the composition of households seems to be important. Increasing the average age of household members is associated with higher welfare. This is not surprising as an increase in the average age of household members implies more working hands to generate income. As expected, asset ownership predicts higher welfare, as shown by the positive association between livestock ownership and household welfare.

4.2. Urbanisation and composition of household welfare

In this section, we report the results and the effects associated with our secondary outcome of interest, the share of non-food consumption. Such analysis is relevant for several reasons. First, the evolution, composition and dimension of household welfare are informative about eventual structural transformation and hence the development perspectives of a country. Structural transformation and overall economic growth are usually associated with a change in consumption structure and patterns (Dercon and Gollin, 2014), usually manifested through a reduction in the share of household budget allocated to food combined with an increase in budget spent on non-food items. Furthermore, urban growth may also facilitate access to important goods and services, which in turn may increase household spending on various dimensions of welfare, including on education, which can have significant long-term effects.

In Tables 6–7, we present results characterising the dynamics in the share of non-food consumption as a function of urban growth as well as other household and community-level controls. The results in Table 6 use mean nightlight intensity, while those in Table 7 are based on total (sum) nightlight intensity. The findings reported in Tables 6–7 clearly show that an increase in nightlight intensity is significantly associated with an—increase in non-food consumption and hence an increase in the share of non-food consumption in overall welfare. For example, the results in Table 6 show that a one radiance increase in average nightlight intensity in an EA (which requires tripling the latest round mean nightlight intensity reported in Table 3) increases the share of non-food consumption by about ten percentage points. We further disaggregate this in the next section and show that the impacts are slightly stronger for rural areas/small towns.

Overall, the results in Tables 6–7 show that besides improving overall welfare, urbanisation can shape the composition and hence affect various dimensions of household welfare differently. This may be driven by the income effect of urbanisation or the supply-side amenities associated with urban expansion. Unlike rural areas, urban centers provide better amenities that are welfare-enhancing in the short and long term. For instance, urban areas have better labor market prospects in terms of employment in high-productivity sectors such as manufacturing and services sectors that pay better salaries and wages. The increase in incomes allows households to spend on amenities such as schools, the internet, electricity, hospitals and other non-food consumption. Therefore, the results suggest that urbanisation is associated with short-term welfare improvement and potentially long-term welfare, as measured by an increased proportion of spending on human capital-related consumptions (education). While non-food consumption includes many items, like unhealthy consumption items (cigarettes, alcohol), we do not have a reason to believe that spending on these unhealthy items outweighs spending on productive items (e.g., education). Regardless, the evidence that urbanisation is associated with improved non-food and overall consumption can inform urban welfare programs in the rapidly urbanising world.

Table 6: Urbanisation and Composition of Household Welfare: Using Mean Nightlight Intensity

	(1) Share of non-food consumption	(2) Share of non-food consumption	(3) Share of non-food consumption	(4) Share of non-food consumption
NTL (mean)	0.0982**	0.1053	0.0989**	0.1055
	(0.0474)	(0.0719)	(0.0481)	(0.0724)
Sex of head of household			−0.0026	0.0225
			(0.0044)	(0.0349)
Ln(age of head of household)			−0.0449***	−0.0581**
			(0.0082)	(0.0293)
Education head (dummy)			0.0301***	0.0086
			(0.0039)	(0.0101)
Household size			0.0022**	0.0011
			(0.0011)	(0.0054)
Ln (average age in household)			0.0130*	0.0033
			(0.0075)	(0.0162)
Farm size (ha)			−0.0000**	−0.0001**
			(0.0000)	(0.0000)
Urban (dummy)			0.0000	0.0000
			(0.0000)	(0.0000)
Ln (TLU)			0.0059**	0.0032
			(0.0027)	(0.0052)
Non-farm income (dummy)			0.0057	0.0084
			(0.0045)	(0.0110)
Access to micro finance			0.0009	−0.0012
			(0.0074)	(0.0096)
Access to formal credit (borrowed from formal source)			0.0001	−0.0027
			(0.0049)	(0.0101)
Enumeration area FE	Yes	—	Yes	—
Household fixed effects	No	Yes	No	Yes
Year dummies	Yes	Yes	Yes	Yes
R-squared	0.3470	0.6562	0.3654	0.6574
No. observations	11,436	11,436	11,436	11,436

Source: Authors' calculations based on data from the ESS 2011/12, 2013/14 and 2015/16.

Notes: NTL stands for nightlight intensity. In this table, we employed mean radiance within a buffer zone of a 10 km radius. 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.

5. Heterogenous effects of urbanisation

This section aims to contribute to evolving debates on the differential roles of urbanisation in poverty reduction in developing countries. The first debate revolves around whether governments should invest in small towns or major cities to reduce poverty (e.g., Christiaensen *et al*., 2013; Christiaensen and Kanbur, 2017; Gibson *et al*., 2017). There exists an interesting debate whether governments should shift public investments towards secondary towns from big cities to reduce poverty sustainably. Although the distinction between secondary towns and cities appears to be unclear and less informative (because urbanisation is often a continuum process than dichotomous evolution), two mechanisms are at play, probably

Table 7: Urbanisation and Composition of Household Welfare: Using Total Nightlight Intensity

	(1) Share of non-food consumption	(2) Share of non-food consumption	(3) Share of non-food consumption	(4) Share of non-food consumption
NTL (sum)	0.0001**	0.0001	0.0001**	0.0001
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Sex of head of household			−0.0026	0.0225
			(0.0044)	(0.0349)
Ln (age of head of household)			−0.0449***	−0.0581**
			(0.0082)	(0.0293)
Education head (dummy)			0.0301***	0.0086
			(0.0039)	(0.0101)
Household size			0.0022**	0.0011
			(0.0011)	(0.0054)
Ln(average age in household)			0.0130*	0.0033
			(0.0075)	(0.0162)
Farm size (ha)			−0.0000**	−0.0001**
			(0.0000)	(0.0000)
Urban (dummy)			0.0000	0.0000
			(0.0000)	(0.0000)
Ln (TLU)			0.0059**	0.0032
			(0.0027)	(0.0052)
Non-farm income (dummy)			0.0057	0.0084
			(0.0045)	(0.0110)
Access to micro finance			0.0009	−0.0012
			(0.0074)	(0.0096)
Access to formal credit			0.0001	−0.0027
(borrowed from formal source)			(0.0049)	(0.0101)
Enumeration area FE	Yes	—	Yes	—
Household fixed effects	No	Yes	No	Yes
Year dummies	Yes	Yes	Yes	Yes
R-squared	0.3470	0.6562	0.3654	0.6574
No. observations	11,436	11,436	11,436	11,436

Source: Authors' calculations based on data from the ESS 2011/12, 2013/14 and 2015/16.

Notes: NTL stands for nightlight intensity. In this table, we employed total (sum) radiance within a buffer zone of 10 km radius. Estimates were adjusted for sampling weights. Standard errors, clustered at the enumeration-area level, are given in parenthesis. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

generating differential welfare impacts across large cities and small towns. First, public investments in large cities and small towns may have differential effects. For instance, Dorosh and Thurlow (2013) show that redirecting public investment towards towns rather than cities generates higher growth and poverty reduction effects. Similarly, Datt *et al*. (2016) find that the growth of secondary towns is associated with higher rural poverty reduction than the growth of cities. Second, some studies argue that migration to small towns may have a higher welfare impact than migrating to cities (e.g., Ingelaere *et al*., 2018; Christiaensen *et al*., 2019a; Christiaensen *et al*., 2019b; Christiaensen and Kanbur, 2017).

Table 8: Heterogeneity: Effect of Urbanisation on Welfare, by Large Towns Versus Small Towns and Rural Areas

Explanatory variables	(1) Log (real consumption)	(2) Log (real consumption)	(3) Log (real consumption)	(4) Log (real consumption)
Panel A: rural areas and small towns				
NTL (mean)	0.7532***	0.7737**	0.4519**	0.5927**
	(0.2886)	(0.3407)	(0.2252)	(0.2785)
R-squared	0.3081	0.6452	0.3779	0.6564
No. observations	9,396	9,396	9,396	9,396
Panel B: medium and large towns				
NTL (mean)	0.1648	0.2265	0.1711	0.1843
	(0.1751)	(0.3059)	(0.1725)	(0.2858)
R-squared	0.2532	0.7843	0.3390	0.7913
No. observations	2,040	2,040	2,040	2,040
Household characteristics	Yes	Yes	Yes	Yes
Enumeration area FE	Yes	—	Yes	—
Household fixed effects	No	Yes	No	Yes
Year dummies	Yes	Yes	Yes	Yes

Source: Authors' calculations based on data from the ESS 2011/12, 2013/14 and 2015/16.

Notes: NTL stands for nightlight intensity. In this table, we employed mean radiance within a buffer zone of a 10 km radius. Estimates were adjusted for sampling weights. Standard errors, clustered at the enumeration-area level, are given in parenthesis. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

The second debate that this section aims to contribute to is the distributional impact of urban growth across poor and rich households. This is crucial to understand the overall and differential welfare implication of urban development programs in Africa in general and Ethiopia in particular. If urban growth benefits limited groups of societies and households, this may generate welfare inequalities among communities. The following two sub-sections provide evidence that contributes to the above two debates on the differential and distributional impacts of urban growth. In Section 5.1, we split the sample into rural areas/small towns and medium and large towns and estimate our main fixed effects regressions for each sample. We run this exercise on both our outcomes, welfare and the share of non-food consumption. In section 5.2, we run fixed-effects quintile regressions to identify potential differential impacts across the households' welfare distribution.

6. The urbanisation effect is larger in rural areas and small towns

Panel A of Table 8 provides fixed effects results for rural areas and small towns, while Panel B of Table 8 provides corresponding results for medium and large towns. We note that our distinction between large and small towns is simply for exploratory purposes and follows the CSA of Ethiopia's definition. The CSA defines small towns as urban areas with a population of less than 10,000, while large towns are those with a population of 10,000 and above. Thus, our definition and classification may not fit with the broader secondary town versus cities definition commonly used. However, it can serve the exploratory heterogenous analysis we pursue in this section.

Table 9: Heterogeneity: Effect of Urbanisation on the Share of Non-Food Consumption, by Small Towns/Rural Areas Versus Medium/Large Towns

Explanatory variables	(1) Share of non-food consumption	(2) Share of non-food consumption	(3) Share of non-food consumption	(4) Share of non-food consumption
Panel A: rural areas and small towns				
NTL (mean)	0.1315***	0.1362***	0.1242***	0.1313**
	(0.0370)	(0.0507)	(0.0382)	(0.0518)
R-squared	0.2761	0.5798	0.2979	0.5816
No. observations	9,396	9,396	9,396	9,396
Panel B: medium and large towns				
NTL (mean)	0.1531**	0.1329	0.1463**	0.1336
	(0.0661)	(0.1208)	(0.0673)	(0.1201)
R-squared	0.1564	0.7052	0.1909	0.7091
No. observations	2,040	2,040	2,040	2,040
Household characteristics	Yes	Yes	Yes	Yes
Enumeration area FE	Yes	—	Yes	—
Household fixed effects	No	Yes	No	Yes
Year dummies	Yes	Yes	Yes	Yes

Source: Authors' calculations based on data from the ESS 2011/12, 2013/14 and 2015/16.

Notes: NTL stands for nightlight intensity. In this table, we employed mean radiance within a buffer zone of a 10 km radius. Estimates were adjusted for sampling weights. Standard errors, clustered at the enumeration-area level, are given in parenthesis. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

The results in Table 8 clearly show that an increase in nightlight intensity significantly improves household welfare in rural areas and small towns, but no statistically significant effect is found in medium and large towns. The size of the coefficients for rural areas and small towns are more than threefold than those for medium and large towns. In Table A2 we report consistent results using the total (sum) of nightlight intensity associated with each EA. This appears to be consistent with the evolving literature arguing that investments in secondary towns can be more effective in poverty reduction efforts than similar investments in cities (e.g., Dorosh and Thurlow, 2013, 2014; Datt *et al*., 2016; Christiaensen and Kanbur, 2017).

The estimates in Table 9 provide impacts of urban expansion on the composition of household consumption, namely on the share of non-food consumption. Table A3 (in the Appendix) provides similar results using the total (sum) of nightlight intensity associated with each EA. These results show that an increase in nightlight intensity significantly increases the share of non-food consumption in household welfare, both for rural and small towns as well as for medium and large towns. This implies that the additional welfare gains associated with urban growth are translated into increases in non-food consumption. No significant difference is found between the urbanisation effect on the consumption structure between rural areas/small towns and medium/large towns, even though the coefficients are significantly more robust in the former. This can be justified by diminishing returns to urban growth or similar patterns in the Engel's curve (i.e., non-food share increases faster at low levels of income).

Two features of our data and sample make our findings particularly interesting for African urban-development programs and policy. First, the type of urbanisation we study is not the kind of urbanisation that typically leads to the creation of major towns and cities but rather to the expansion of small towns. The significant welfare impacts associated with this small-scale urban growth are encouraging and may justify public investments in small towns. Second, the time horizon we are covering is relatively short, and many of the effects we document are short-term impacts, though they could accumulate over the longer term.

7. The urbanisation effect is larger for richer households

The effect of urbanisation (on welfare and consumption structure) may differ across welfare distribution and hence across poor and rich households. Such heterogeneity is indeed depicted in Figure 2, which reports the quantile regression results when the outcome is welfare (top panel) or the share of non-food consumption (bottom panel). The top panel shows an increasing pattern of the urbanisation effect across the whole welfare distribution. When we use the whole sample (panel on the left), the coefficients are always statistically significant irrespective of the welfare percentile. The analyses by rural areas/small towns and medium/large towns show that the effect is statistically significant only between the 40th and 80th percentiles in both cases. This may suggest that poorer households may not sufficiently benefit from urban growth because of the type of sector where they are engaged or the type of assets they dispose of. For households in the highest percentiles, the corresponding position on the urbanisation-welfare curve might be where the marginal returns are very small (due to diminishing returns). However, the disaggregated results need to be read cautiously because the low number of observations by deciles imposed by the quantile regressions increases the standard errors and makes the estimates less precise.

Moving to the bottom panel of Figure 2, we find that the size of the urbanisation coefficients increases across percentiles of non-food consumption share in the full sample and rural areas/small towns sub-sample. However, in both cases, the effect of urban growth on the share of non-food consumption appears to be statistically significant only in the 25th–65th percentiles. This is compatible with the hypothesis that a marginal increase in urbanisation among the poorest percentiles would not be enough to allow them to divert additional budget away from food consumption. Moving to those households in medium and large towns, the bottom panel on the right shows a steeper positive relation, with significant effects from the 30th percentile. Overall, these quantile regression results may indicate that the urbanisation pattern observed in Ethiopia between 2011 and 2016 might have increased welfare inequalities within and across the Ethiopian regions.

8. Robustness exercises

To probe the robustness of our main results and hence address some identification threats, we conduct the following empirical tests and important empirical exercises to address two identification threats. First, even though households have limited control over urban growth, they might endogenously sort their residences through migration decisions. Households might migrate to areas that are urbanising or to areas with higher labour-market potential. To explore whether such endogenous migration patterns drive our main results, we restrict our sample to those households who had lived in the area for a long time. In particular, we

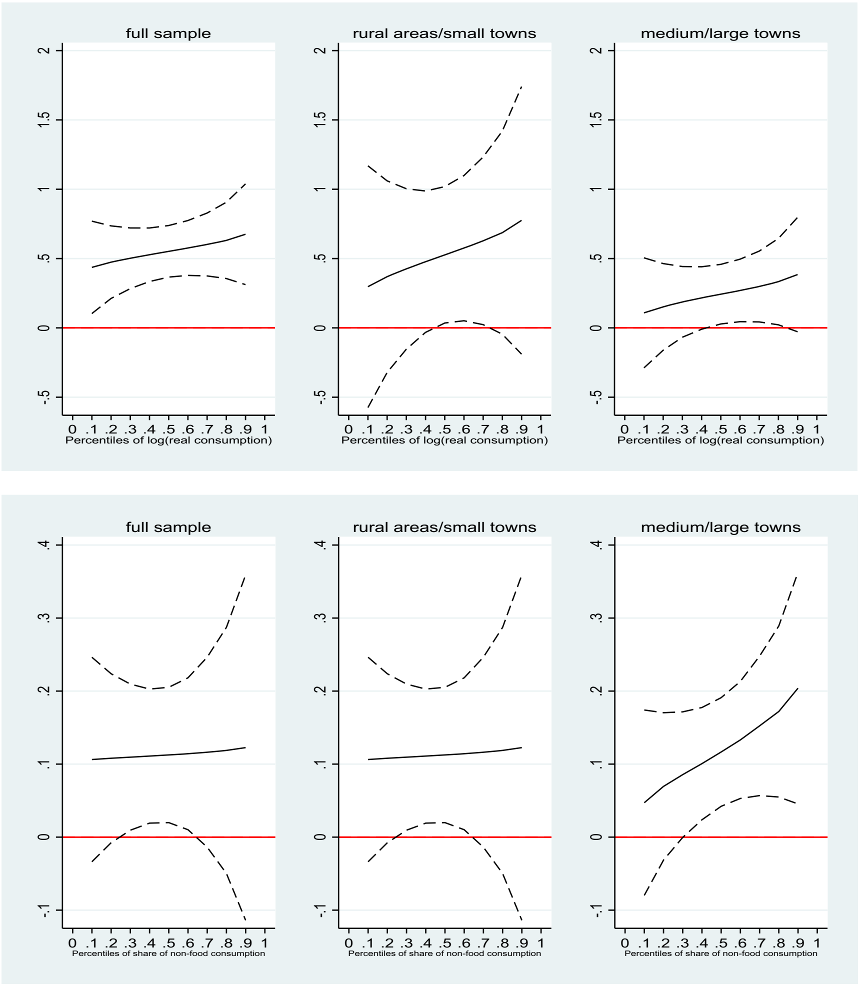

Figure 2: Heterogeneity in Impacts Across Welfare Distribution (Quintile Regression): Using Mean Night Light Radiance. *Source*: Authors' calculations based on data from the ESS 2011/12, 2013/14 and 2015/16. *Notes*: Estimates are based on the Stata command *xtqreg*, which allows to run quantile regressions by controlling for fixed effects. However, the command does not allow weighting the estimations by the sampling weight (so the average coefficients reported in Table 4 cannot be directly compared with these figures).

excluded recent migrants, estimating similar regressions. Table 10 provides these estimates, which are similar to those based on full-sample estimates. This suggests that endogenous selection and migration of some households are not driving much of the effect.

Second, the impact of urban growth may take some time to translate into welfare gains. In this case, the contemporaneous relationship between nightlight intensity and household welfare may not sufficiently capture the delayed impacts of urban growth. Furthermore, the contemporaneous relationship between nightlight intensity and household welfare may capture the effects of other factors accompanying the urbanisation processes. To circumvent

Table 10: Nightlight Intensity and Household Welfare: Excluding Those Households Who Arrived Recently

Explanatory variables	(1) Log (real consumption)	(2) Log (real consumption)	(3) Log (real consumption)	(4) Log (real consumption)
NTL (mean)	0.3059**	0.4064*		
	(0.1389)	(0.2237)		
NTL (sum)			0.0002**	0.0003*
			(0.0001)	(0.0002)
Household characteristics	Yes	Yes	Yes	Yes
Enumeration area FE	Yes	—Yes	Yes	Yes—-
Household fixed effects	No	Yes	No	Yes
Year dummies	Yes	Yes	Yes	Yes
R-squared	0.4048	0.6980	0.4047	0.6980
No. observations	9,080	9,080	9,080	9,080

Source: Authors' calculations based on data from the ESS 2013/14 and 2015/16 for rural and small towns.

Notes: NTL stands for nightlight intensity. In this table, we employed mean radiance within a buffer zone of 10 km radius. 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 11: Nightlight Intensity and Household Welfare: Using Lagged Values of Night Light

Explanatory variables	(1) Log (real consumption)	(2) Log (real consumption)	(3) Log (real consumption)	(4) Log (real consumption)
NTL (mean)	0.1366**	0.1317		
	(0.0564)	(0.0910)		
NTL (sum)			0.0001**	0.0001
			(0.0000)	(0.0001)
Household characteristics	Yes	Yes	Yes	Yes
Enumeration area FE	Yes	—	Yes	—
Household fixed effects	No	Yes	No	Yes
Year dummies	Yes	Yes	Yes	Yes
R-squared	0.4542	0.7889	0.4542	0.7889
No. observations	8,112	8,112	8,112	8,112

Source: Authors' calculations based on data from the ESS 2013/14 and 2015/16.

Notes: NTL stands for nightlight intensity. In this table, we employed mean radiance within a buffer zone of 10 km radius. Estimates were adjusted for sampling weights. Standard errors, clustered at the enumeration-area level, are given in parenthesis. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

these concerns, we lagged the nightlight intensity series by one year and estimated similar fixed-effect specifications. The results in Table 11 broadly show consistent evidence.

9. Conclusions

Despite evolving evidence that Africa is urbanising differently (e.g., Jedwab, 2012; Henderson *et al*., 2013; Gollin *et al*., 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, remain unexplored. This is partly attributable to the lack of objective measures of the level and dynamics of urbanisation. Most previous measures and definitions of urbanisation 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.

In this paper, we employ objective markers of urbanisation to explore the short-term implications of urbanisation in Ethiopia on household welfare. Following recent attempts, we use satellite-based nightlight-intensity data (VIIRS-DNB) to capture urban features and growth over 2012–2016. For such a purpose, we link household-level longitudinal data with satellite-based nightlight intensity. In particular, we apply this new marker of urbanisation to identify and quantify the welfare implications of recent urbanisation trends in Ethiopia. Studying urban-development programs in Ethiopia provides an interesting case for some important reasons. Although starting from a low level of urbanisation, 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 Ethiopian government remains sufficiently vigilant and committed to managing and monitoring current and future urban expansions. However, most of the policy discourse in this regard has not been informed by rigorous evaluations. In an attempt to inform these debates, we merge georeferenced longitudinal household data from the LSMS-ISA and satellite-based time series nightlight-intensity data for Ethiopia. To estimate the causal effect of urbanisation on household welfare, we exploit the longitudinal and spatial variations in our measure of urbanisation and hence estimate household fixed effects models.

We find that urban growth, particularly the expansion of small towns, as measured by nightlight intensity, is associated with significant improvements in household welfare. In particular, we find that tripling nightlight intensity is associated with about a 42–46% improvement in household welfare. This result remains robust to alternative empirical specifications and sources of bias. These improvements in household welfare appear to have been driven by households in rural areas and small towns. We also find that the urbanisation process affected consumption structure, as it contributed to a relatively higher household budget share on non-food consumption.

We also find suggestive evidence that urbanisation is associated with welfare inequality. We show that potential dynamics in urban expansion may trigger welfare inequality among households living in a specific community. Relatedly, we also show significant heterogeneities in the impact of urban growth. Our quantile regressions show that households between the 40th and 80th welfare percentiles were more likely to benefit from urban growth than those in the bottom percentiles.

Our results have important implications for informing 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 and contribute to some structural transformation. Such improvements may not be uniformly distributed, as suggested by the heterogeneous impacts we document, which may increase inequality. These results reinforce the need to regulate and monitor urban expansion in Ethiopia in a way that can benefit larger groups.

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Supplementary material

Supplementary material is available at *Journal of African Economies* online.

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Appendix: Additional Tables

Table A1: The relationship between total welfare and share of non-food consumption

	(1) Share of non-food consumption	(2) Share of non-food consumption	(3) Share of non-food consumption
Log(total consumption)	0.0202***	−0.0025	0.0213**
	(0.0056)	(0.0057)	(0.0106)
Region dummies	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
R-squared	0.0684	0.0191	0.0278
No. observations	11,436	9,396	2,040

Notes: This table tests the association between total welfare and share of non-food consumption (the Engel curve's hypothesis). Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: Heterogeneity: Effect of urbanization on welfare, by large towns versus small towns and rural areas

Explanatory Variables	(1) Log (real consumption)	(2) Log (real consumption)	(3) Log (real consumption)	(4) Log (real consumption)
Panel A: rural areas and small towns				
NTL (sum)	0.0005**	0.0005**	0.0003**	0.0004**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
R-squared	0.3081	0.6452	0.3779	0.6564
No. observations	9,396	9,396	9,396	9,396
Panel B: Medium and large towns				
NTL (sum)	0.0001	0.0002	0.0001	0.0001
	(0.0001)	(0.0002)	(0.0001)	(0.0002)
R-squared	0.2532	0.7843	0.3390	0.7913
No. observations	2,040	2,040	2,040	2,040
Household characteristics	Yes	Yes	Yes	Yes
Enumeration area FE	Yes	-	Yes	-
Household fixed effects	No	Yes	No	Yes
Year dummies	Yes	Yes	Yes	Yes

Source: Authors' calculations based on data from the ESS 2011/12, 2013/14 and 2015/16.

Notes: NTL stands for nightlight intensity. In this table, we employed total (sum) radiance within a buffer zone of 10 km radius. 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 A3: Heterogeneity: Effect of urbanization on the share of non-food consumption, by small towns/rural areas versus medium/large towns

Explanatory Variables	(1) Share of non-food consumption	(2) Share of non-food consumption	(3) Share of non-food consumption	(4) Share of non-food consumption
Panel A: rural areas and small towns				
NTL (mean)	0.0001***	0.0001***	0.0001***	0.0001**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
R-squared	0.2761	0.5798	0.2979	0.5816
No. observations	9,396	9,396	9,396	9,396
Panel B: Medium and large towns				
NTL (mean)	0.0001**	0.0001	0.0001**	0.0001
	(0.0000)	(0.0001)	(0.0000)	(0.0001)
R-squared	0.1564	0.7052	0.1909	0.7090
No. observations	2,040	2,040	2,040	2,040
Household characteristics	Yes	Yes	Yes	Yes
Enumeration area FE	Yes	-	Yes	-
Household fixed effects	No	Yes	No	Yes
Year dummies	Yes	Yes	Yes	Yes

Source: Authors' calculations based on data from the ESS 2011/12, 2013/14 and 2015/16.

Notes: NTL stands for nightlight intensity. In this table, we employed total (sum) mean radiance within a buffer zone of 10 km radius. Estimates were adjusted for sampling weights. Standard errors, clustered at the enumeration-area level, are given in parenthesis. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.