



# Does Urban Agriculture Help to Win the Battle Against Food Insecurity? Evidence from City Administrations of Gurage Zone, Southern Ethiopia

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## ABSTRACT

With the rise in capital wealth and human populations, cities need more food input. This study assessed the impact of urban agriculture on improving food security in four town administrations of Gurage Zone. Qualitative and quantitative data were collected from primary and secondary sources. The primary data was collected from 340 sampled adopters using interviews, focus group discussions, and observation. Chi-square and t-tests enabled comparisons among percentages and mean differences between adopters and non-adopters of urban agriculture. The propensity score matching (PSM) model enabled an assessment of the urban agricultural impact on food security. The statistical analysis revealed a statistically significant mean difference between adopters and non-adopters in job status, perception toward urban agriculture, and family size. The logit model showed that family size, ownership of living home, job status of HH head, perception toward urban agriculture, market demand, and training and support significantly determined the adoption of urban agriculture. The results of PSM indicated that adopting urban agriculture improved food security. Thus, the likelihood of being food secure would increase by a factor of 0.60, *ceteris paribus*. The study suggested that education, urban agriculture, and cooperative offices can teach urban dwellers via an integrated functional adult education program for training purposes and support them more in cooperative organization. The adoption of urban agriculture helps to win the battle against food insecurity.

## Introduction

High food costs and low food reserves are two factors that seem to be contributing to the global food crisis, especially in developing countries. A significant portion of the human population lives in towns and cities, and their numbers may well reach 5 billion by 2030. Africa and Asia will unfold much of this urbanization, thus bringing social,

economic, and environmental transformations (UNPF, 2020). In 2021, the GC urban population of Ethiopia was 22.2%, and over the last 50 years, the human population that lived in towns and cities in Ethiopia grew ominously from 8.9 to 22.2% (Knoema, 2020).

Basic citizen needs can become undermined due to the rapid growth of cities and towns. Previous studies have indicated that urban poverty rates

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are high and on the rise. There is always a risk and susceptibility for an underdeveloped urban population that works in the formal or unofficial sectors, and their jobs are insecure. The underdeveloped urban population spends a large portion of its income on food, leaving them vulnerable to shifting macroeconomic conditions. They are also more likely to be exposed to disease because they live in dense populations. Thus, this rapid urbanization leads to the question of food security and urban poverty (Palanivel, 2017).

The 2019 global Multidimensional Poverty Index (MPI) shows that 83.8% of the Ethiopian population is in multidimensional poverty. FAO (2019) has indicated that more than 8.1 million people require food assistance in Ethiopia (Abduselam, 2017).

Food insecurity and undernutrition remain primary issues in many nation-states despite attempts that continue to address these issues globally (Sibhatu, 2017). Even though achieving food security is appealing regardless of the political condition and socioeconomic situation (Jerzak et al., 2020), it is of the utmost importance in the developing world where population growth and an intensified occurrence of natural disasters frequently pose threats to food security (Ahmed et al., 2017). Optimizing management and practices in the agricultural sector is an essential prelude to consistent food availability and food security. There is ambiguity over the global agricultural ability to meet this need by increasing the food supply, even though it is generally agreed that the demand for food will expand globally in the next decades (Cook et al., 2011).

Agriculture is the first source of revenue for 85% of Ethiopians, making it the most important economic sector in the nation. However, due to its low productivity, it cannot meet entire demands for food security (FAO, 2016). Farming practices used in the country, including primary agricultural regions, are known as mixed farming, aiming to raise animals such as chicken, cattle, and small ruminants in addition to cereal crops, pulse crops, and horticultural crops.

According to the previously mentioned idea of food security, Ethiopia is one of the most food-insecure and aid-dependent nations. Many Ethiopians have experienced chronic and temporary food shortages, particularly in recent decades, where urban and rural locations are populated. While the amount of food available per person has decreased, the number of households experiencing food insecurity has risen. This relationship shows that for more than 40 years, the per capita food supply remained substantially below the minimum necessary level. Imports of

food and food aid, the latter of which made up the bulk of the shortfall, partially addressed the significant imbalance between food supply and demand. At this point, one can ask what urban agriculture is and how it contributes to achieving food security (Tefera, 2010).

Urban agriculture describes the activity of growing, preparing, and distributing food in or near urban areas. The urban food system and local economies benefit from multiple techniques, including community gardens, vertical farming, and rooftop gardens, each of which has a unique impact. One of the methods for attaining sustainable agriculture and food security for urban residents is a crucial tactic for guaranteeing that every home gets enough fresh produce (Hayuningtyas, 2017). With the versatility of urban agriculture, urban residents may contribute to sustainable urban development by having multiple options for work, income, and food choices in addition to recycling and reusing urban garbage. Despite its potential, institutional and policy support for the sector remains insufficient (Yalew, 2020).

Nowadays, studies have looked at the benefits of urban agriculture as it relates to food production, dietary patterns, and food security. Research has indicated a positive association between those who have grown food and create consumption demand (Van Lier et al., 2017). It contributes to better health and well-being, while home gardening provides increased access to affordable and nutritious produce to improve food security for the community (Walljasper and Polansek, 2020; Akinngbe and Ipinmoye, 2022).

Many argue that the principal reason that makes people engage in urban agriculture is in response to inadequate, unreliable, and irregular access to food supplies. Moreover, over the past ten years, there has been tremendous growth in interest and activity in urban agriculture (Hallett et al., 2016). Urban agriculture could become an instrument that could tackle household food insecurity if directed correctly at enhancing urban food production and employment. Moreover, urban agriculture is an increasingly acceptable, affordable, and effective tool for sustainable urbanization (Palanivel, 2017; Akinngbe and Ipinmoye, 2022). Previous studies in sub-Saharan Africa indicated that many low-income and higher-income households turn to urban agriculture to establish homely consumption (Christopher, 2018).

Likewise, urban agriculture is emerging in Africa and nations such as Ethiopia. However, it is not growing in number and quality as expected. Moreover, few studies have addressed the benefits of urban agriculture on food production,

dietary patterns, and food security. However, empirical studies remain scanty on the impact of urban agriculture in improving food security in the Gurage Zone. Accordingly, we attempted to determine how much the struggle against food insecurity among urban residents in Gurage Zone towns can benefit from urban agriculture.

## Materials and Methods

### Study area description

Gurage zone is part of the newly established Central Ethiopia Regional State (Fig. 1). It is

bordered by Hadiya, Silti, Yem Special Woredas and Oromia Region. The total population of the Zone is 1.576, of which 11% is urban (CSA, 2018). Topographically, the zone lies within an elevation ranging from 1000 to 3600 m above sea level, with annual average temperature ranging from 13 °C to 30 °C, and the mean annual rainfall ranges from 600 to 1600 mm. Gurage zone has three agroecological zones namely, lowland, midland, and highland. There are five Town administrations in the zone, i.e., Butajira, Wolkite, Buie, Gunchire, and Emdibir.

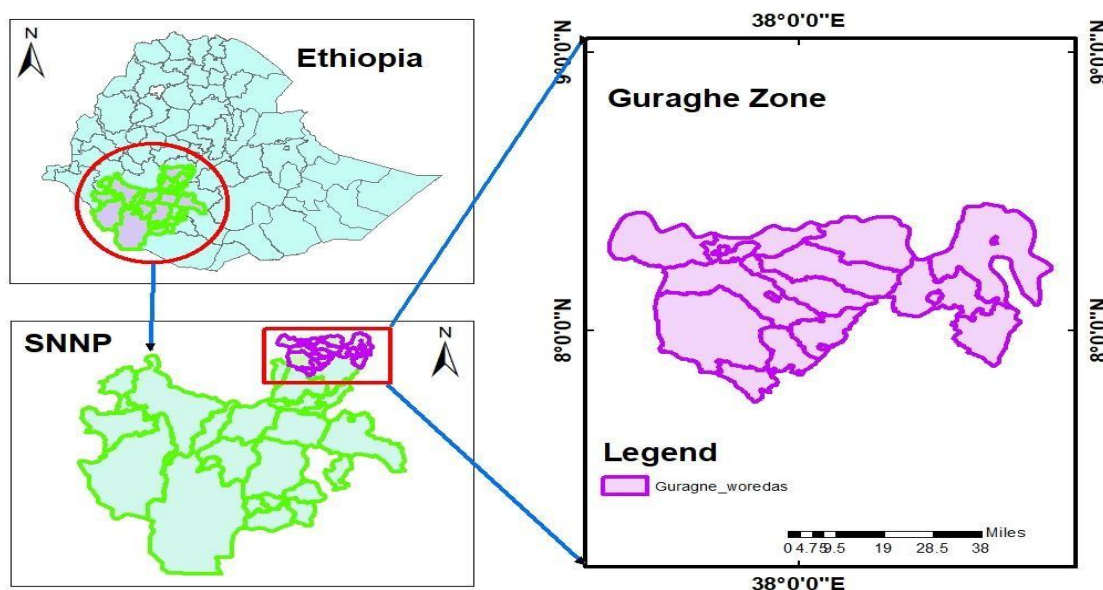


Fig. 1. Study area map.

### Data type, sources, and sampling procedure

Qualitative and quantitative data were collected from primary and secondary sources. The primary data were collected from urban farming and non-farming households. The secondary data were collected from reports by the agriculture offices, unions, cooperatives, and published documents/articles. Three-stage sampling techniques were applied to select the representative sample households. In the first stage, the existing four town administrations in the zone were selected, i.e., Butajira, Wolkite, Buie, and Emdibir (GZoANR, 2020). In the second stage, two representative kebeles from each town were identified and selected purposively based on their potential. Thirdly, the sample households were drawn from each kebeles proportional to their population size. The sample size was determined using Cochran (1963), with a 5% level of precision ( $P \leq 0.05$ ).

$$n = \frac{Z^2 PQ}{e^2} = \frac{0.5 * 0.5 * 1.96^2}{0.05^2} = 340$$

Where, Z is the estimated proportion of an adopters in the population, Q = 1-P, n = sample size and e = precision level.

### Methods of data collection and data analysis

Data collection methods: Survey/interview, focus group discussion, and observation were done in 2022. To collect the primary data, a semi-structured questionnaire was prepared. It was collected by asking key informants (6) who had experience and knowledge about the subject. The checklist was prepared for focus group discussion and distributed to 10 individuals from each Kebeles. The secondary data were collected by reviewing published documents and agricultural reports in the district.

Both descriptive and econometric analyses were used. Details of explanations about these methods

are discussed as follows. Descriptive statistics such as mean, minimum and maximum value, frequency, percentages, and standard deviation were used for analyzing the socioeconomic characteristics of the sample households. Chi-square and t-tests enabled the comparison of percentages and mean differences between adopters and non-adopters of urban agriculture. Following Amare A (2017), the food security status of the sample household was measured by passing the following procedure. The net food grains available for each household in kilograms were converted to equivalent total kilocalories using a conversion factor for Ethiopia (Agren and Gibson, 1968). Then, the food supply at the household level calculated in step one was used for calculating calories available per person per day for each household. Then, following the FDRE Food Security Strategy, 2,100 kilocalories per person per day was used as a measure of calories required (i.e., demand). This amount is enough to enable an adult to live a healthy and moderately active life. Finally, a comparison between the available (supply) and required (i.e., demand) grain food was made. Using 2,100 kilocalories as the cut-off point, a household whose available daily per capita calories (supply) are less than their demand was considered food insecure. Those who had ample calories available daily per capita were considered food secure.

### ***Econometric analysis and impact of urban agriculture on the food security status of households***

According to the literature, impact assessment studies based on cross-sectional data were evaluated by the propensity score-matching model. This situation holds if the households have similar characteristics except for the treatment variable (Heckman et al., 1998). Similarly, in this study, the propensity score matching (PSM) model assessed the impact of urban agriculture on food security. In applying the PSM, the adopters of urban agriculture were matched with the non-adopters based on the propensity score, and the household food security status was the outcome variable. Accordingly, the propensity score, as the conditional probability of receiving the treatment given the pre-treatment variables, was estimated first by the Logit model, following Ahmed and Mesfin (2017). Accordingly, the Logit model extracted factors that affected the adoption of urban agriculture.

The common support region was within the minimum and maximum propensity scores of treated groups (adopters of urban agriculture) and comparison groups (non-adopters).

Matching algorithms defined the average treatment effect (Caliendo and Kopeinig, 2008). Accordingly, the nearest neighbor, radius matching, and Kebeles appeared effective in this study. The average treatment effect (ATE) was the difference in the mean outcome of the matched adopters and non-adopters of urban agriculture, with support conditional on the propensity score. Finally, sensitivity analysis enabled an assessment of how the finding of this study was free from hidden bias. The basic question to be answered here is whether inference about treatment effects may be altered by unobserved factors. It is not possible to estimate the magnitude of selection bias with non-experimental data. The problem can be addressed by sensitivity analysis (Caliendo and Kopeinig, 2008). To check for unobservable bias, the Rosenbaum Bounding approach (Rosenbaum, 2002) sensitivity analysis was apt on the computed outcome variables concerning deviation from the conditional independence assumption.

### ***Definition of variables***

The dependent variable for applying the Logit model is the adoption of urban agriculture. The outcome variables are food security status from practicing urban agriculture. The independent variables are identified based on the previous research and the conditions of the study area. The independent variables are age, sex, education level, job status, monthly income of the household, family size, land size, perception of urban agriculture, credit access, training and support, ownership of living home, market demand, and household location.

### ***Dependent variable***

Practice of urban agriculture: a dummy variable given a value of 1 for adopters and 0 for non-adopters.

### ***Outcome variables***

#### ***Independent variables***

Age of the household head (AGHH): a continuous variable measured in years. This variable is hypothesized as a positive or negative effect on the adoption of urban agriculture based on previous findings (Ngahdiman et al., 2017; Asfaw et al., 2012). The main reason behind this could be the younger/older the farmers are, the less likely the farmers are adopters of urban agriculture due to lack of information about urban agriculture. However, when the age of the household head is within the productive age, the variable is expected to have positive effects on the

adoption of urban agriculture.

**Sex of household head (SEXHH):** a dummy variable that takes the value of 1 if the household head is male and 0 if the household is female. Sex difference is a factor affecting the adoption of new practices. Males have better opportunities to move outside their house and participate in different developmental programs than females. Thus, men can have more information and knowledge to adopt technology. However, most urban farmers are female (Nghadiman et al., 2017). Nevertheless, in this study, it is hypothesized that male farmers are more likely to adopt practices of urban agriculture.

**Educational status of household head (EDHH):** a categorical variable, which takes 0 for illiterate, 1 for primary, 2 for secondary, and 3 for college and above. It is assumed that educated households are more likely to adopt urban agriculture, whereas illiterate households are less likely to adopt these varieties due to a lack of knowledge or awareness about urban agriculture. Thus, this variable is hypothesized to affect adoption likelihood. According to Ibrahim et al. (2020), education for the household is the main factor affecting the adoption of urban agriculture.

**Family size (FAMSZ):** a continuous variable measured in the number of individuals within the household. Different literature indicated that the number of individuals in the household could have either positive or negative effects on the adoption of new technology. Urban dwellers with bigger households are likely to have intentions to practice urban agriculture (Nghadiman et al., 2017). This could be due to helping hands among family members. Thus, it is hypothesized that it has a positive effect on the adoption of urban agriculture.

**Land size (LASZ):** a continuous variable measured by hectare. It has a positive relationship with the adoption of urban agriculture. As the land size increases, the probability of practicing urban agriculture is expected to increase. This relationship is because households that own large lands can have enough space to practice urban agriculture. According to Lamichhane et al. (2018), the land size has positive effects on adoption of the agricultural technology. Therefore, this variable is expected to have a positive and significant effect on the adoption of urban agriculture.

**Job-status of household head (JSHH):** a dummy variable taking the value of 0 for unemployed people (job seekers) and 1 for the employed. This variable is hypothesized to have negative influences on the adoption of urban agriculture. This is because households who have other income-generating jobs are less likely to adopt

urban agriculture. Therefore, it is theorized to have negative and significant effects on the engagement of urban agriculture.

**Monthly income of the household (MOINHH):** a continuous variable measured by Ethiopian birr. This variable is expected to have a negative and significant effect on the engagement of urban agriculture. The main rationale behind the negative effects of this variable is that if the household had better monthly income it is less likely to practice agriculture in the urban source of income.

**Perception of households toward urban agriculture (PHUA):** a dummy variable that assumes that (1) urban agriculture can reduce the cost of buying and (0) it cannot. Therefore, it is hypothesized that perception toward urban agriculture would positively affect engagement. Perceiving the practice of urban agriculture can reduce the cost of buying fresh food and promote healthy eating habits (Grebitus et al., 2020).

**Credit access (CRAC):** a dummy variable that takes the value 1 if the household has access to credit and 0 otherwise. Farmers who have access to credit may overcome their financial constraints and engage in urban agriculture. Farmers without cash and credit access may find it difficult to adopt technology (Konja, 2022).

**Household Location (HHLO):** the location where the household resides. It is a categorical variable measured by the difference in location of HH. It represents the model as  $\rho_1$  for those households who live in Butajira,  $\rho_2$  for households in Wolkite,  $\rho_3$  for households in Buie, and  $\rho_4$  for households in Emdibir. Regional differences can influence farmer adoption decisions (Kikulwe et al., 2019).

**Training and support (TRSU):** a continuous variable measured in the number of training and support provided by the government and NGOs to the HH regarding urban agriculture. It is known that training provides information to a household and enables its adaptive technology. Accordingly, it is hypothesized that training and support would improve engagement of training and support.

**Ownership of living home (OWLHO):** a dummy variable that takes the value 1 if the household has its own home and 0 otherwise. House ownership can enhance household well-being and the likelihood of adopting urban agriculture (Shinbrot et al., 2019).

**Market demand (MKTDD):** a dummy variable that assumes 1 if there is a growing demand for agricultural products and zero if not. Growing demand for agricultural products provides an incentive for farmers to participate in urban agriculture (Grebitus et al., 2020). Therefore, it is hypothesized that the growing market demand would positively influence engagement.

## Results and Discussion

### *Sociodemographic and economic characteristics of sample households*

Out of 340 sample households, 182 (53.53%) respondents were practicing urban agriculture, while the remaining 154 (46.47%) respondents were not (Table 1). The different variables determining the adoption of urban agriculture are summarized descriptively in Table 1. The Chi2 test (for dummy variables) and t-test (continuous

variables) compared the adopters and non-adopters of urban agriculture (Tables 1 and 2). The statistical analysis revealed a statistically significant mean difference between adopters and non-adopters in job status, perception toward urban agriculture, and family size. Regarding the remaining variables, there was no significant mean difference between the adopters and non-adopters.

**Table 1.** Socio-demographic characteristics of sample households (dummy variables).

| Adopters<br>(N =182) (53.53%) | Non-adopters<br>(N =158) (46.47%) | Chi square |       |     |       |         |
|-------------------------------|-----------------------------------|------------|-------|-----|-------|---------|
|                               |                                   | N          | %     | N   | %     |         |
| Sex                           | Male                              | 126        | 37.05 | 116 | 34.12 | 0.36    |
|                               | Female                            | 56         | 16.47 | 42  | 12.35 |         |
| Homeownership                 | Yes                               | 122        | 35.88 | 94  | 27.64 | 1.038   |
|                               | No                                | 60         | 17.64 | 64  | 18.82 |         |
| Credit access                 | Yes                               | 110        | 32.35 | 84  | 24.70 | 0.91    |
|                               | No                                | 72         | 21.17 | 74  | 21.76 |         |
| Job status                    | Yes                               | 58         | 17.05 | 68  | 20    | 2.26**  |
|                               | No                                | 124        | 36.47 | 90  | 26.47 |         |
| Perception                    | Yes                               | 70         | 20.59 | 6   | 1.76  | 7.18*** |
|                               | No                                | 112        | 32.94 | 152 | 44.71 |         |
| Household location            | 1                                 | 70         | 20.58 | 64  | 18.82 | 1.01    |
|                               | 2                                 | 58         | 17.06 | 40  | 11.76 |         |
|                               | 3                                 | 22         | 6.47  | 24  | 7.06  |         |
|                               | 4                                 | 32         | 9.41  | 30  | 8.82  |         |

Source: survey results 2020/1.

**Table 2.** Socio-demographic and economic characteristics of sample households (continuous variables).

| Variables                       | Adopters (N = 182) |      | Non adopter (N = 158) |       | t-value |
|---------------------------------|--------------------|------|-----------------------|-------|---------|
|                                 | Mean               | SD   | Mean                  | SD    |         |
| Age                             | 42.9               | 0.67 | 41.7                  | 0.76  | -1.19   |
| Family size                     | 5.6                | 0.17 | 5                     | 0.17  | -2.35** |
| Education                       | 3.4                | 0.34 | 3.2                   | 0.32  | -0.42   |
| Land size of residence          | 0.26               | 0.02 | 0.28                  | 0.027 | 0.61    |
| Monthly income of the HH (birr) | 2196               | 55   | 2281                  | 71    | 0.95    |
| Number of training and support  | 3.19               | 0.18 | 2.96                  | 0.18  | -0.91   |

Source: survey result, 2020/1.

Job status is among the most essential factors that can determine the essence of people participation in urban agriculture. The results showed that 37.05% of the total sample households had paying jobs, of which 17.05% were practicing

urban agriculture while the remaining 20% were not. Approximately 63% of the sampled households had no paid job for income, of which 36.47% were adopters of urban agriculture and 26.47% were not. This finding indicated that most

sample households had no paid job as income and had rightly adopted urban agriculture. A statistically significant difference occurred in job status between adopters and non-adopters of urban agriculture ( $P \leq 0.05$ ) (Table 2).

The survey results indicated that 76 sample households (22.3%) believed urban agriculture can reduce their expenses on food purchase, whereas the remainder did not.

Out of 158 non-adopters of urban agriculture, only six believed that urban agriculture can reduce their expenses on food purchase. The differences between adopters and non-adopters of urban agriculture in terms of their perception toward urban agriculture were significant ( $P \leq 0.01$ ) (Table 2).

Egal (2001) and Armar (2001) noted that an increase in the diversity of a household's diet by giving direct access to more nutrient-dense foods can occur by practicing urban agriculture. In contrast to non-agricultural activities, which more likely appear farther away from home, urban agriculture can raise the stability of household food consumption against seasonality or other brief shortages. It can also save time for mothers to spend on childcare.

Family size is a highly essential labor input in every farming activity, and the survey results indicated the average family size was 5.6 in adopter households and 5 in non-adopters. Thus, the results showed that the probability of being an adopter of urban agriculture is higher in large-size families. The mean difference in family size between adopters and non-adopters was statistically significant ( $P \leq 0.05$ ) (Table 2).

### ***Econometric analysis***

#### ***Factors affecting the adoption of urban agriculture***

The logit model indicated that the likelihood function of adopting urban agriculture was highly significant ( $P \leq 0.01$ ) (LR  $\chi^2$  (13) = 30.14 with the probability of  $\text{Prob} > \chi^2 = 0.0045$ ), indicating a strong explanatory power of independent variables to explain factors affecting the adoption (goodness of fitness of the model). The model results revealed that family size, ownership of living home, job status of household head, perception toward urban agriculture, market demand, and training and support from the government and NGOs significantly affected the adoption of urban agriculture (Table 3).

Family size: the number of household members positively and significantly affects the participation in urban agriculture. If the number of individuals/persons within the household

increased by one person, the odds ratio in favor of practicing urban agriculture increased by a factor of 0.32 unit, keeping other variables constant. This result agrees with previous findings by Danso-Abbeam et al. (2017), who found a positive relationship between household size and the adoption of urban agriculture. Moreover, urban dwellers with bigger household sizes are more likely to have intentions to practice urban agriculture (Nghadiman et al., 2017). It could be due to the helping hands among family members. The primary form of urban agriculture wherein households engage differs depending on their size. The findings indicate that as household size increases, backyard gardens become less significant; larger families are typically more involved in open space and urban fringe farming. Homeownership was a significant variable in shaping decisions to practice urban agriculture ( $P \leq 0.1$ ). Compared to households without homeownership, homeowners were more likely to be adopters by a factor of 0.71 units, other variables remaining constant. This finding agrees with previous results by Kaliba et al. (2018) that a positive association exists between this variable and technology adoption. Moreover, homeownership can enhance household well-being and the likelihood of adoption (Shimbrot et al., 2019).

The job status of the household head was a significant factor in the adoption of urban agriculture ( $P \leq 0.05$ ), provided that the odd ratio in favor of adoption would decrease by a factor of 0.95 for households categorized in homeownership. This result contrasts with previous findings in relevant research (Ibrahim et al., 2020) that employment status had a positive and significant effect on practicing urban agriculture. However, households with other income-generating jobs have less time to practice urban agriculture, whereas unemployed people are more likely to be or become urban agriculturists. Moreover, urban agriculture is encouraged by the government as a job-creating opportunity.

Perception toward urban agriculture was a significant variable in determining the decision to practice urban agriculture ( $P \leq 0.01$ ). Households who perceive urban agriculture can reduce the cost of buying. Thus, their chances of adopting urban agriculture would be higher by a factor of 1.74 units, other variables remaining constant. This result agrees with a study done by Nghadiman et al. (2017) that practicing urban agriculture can reduce the cost of buying fresh foods and promote healthy eating.

Market demand was a significant factor in adopting urban agriculture ( $P \leq 0.1$ ), provided

that the odd ratio in favor of adoption would be higher by a factor of 0.82 for households who assume that there is a growing demand for agricultural products. Growing demand for agricultural produce incentivizes farmers to participate in urban agriculture (Greibitus. et al., 2020).

Training and support was significantly variable in

determining the decision to practice urban agriculture ( $P \leq 0.01$ ). If the number of training and support provided to the household increased by one, the odds ratio in favor of practicing urban agriculture would increase by a factor of 0.35, keeping other variables constant. Training provides information to a household that will find capacity to adopt technology.

**Table 3.** Logistic regression estimation result on the factors affecting the adoption of urban agriculture.

| Urban agriculture                   | Coefficient  | Standard error                         | Odds ratio |
|-------------------------------------|--------------|--|------------|
| Age of household head               | 0.0164665    | 0.0352731                              | 1.016603   |
| Sex of household head               | -0.2937674   | 0.2946062                              | 0.7454499  |
| Family size in number               | 0.3187638*** | 0.1629197                              | 1.375426   |
| Education level                     | 0.0798305    | 0.076964                               | 1.083103   |
| Available land for farming          | -0.0518295   | 0.7379808                              | 0.9494907  |
| Homeownership                       | 0.7175692*   | 0.8336504                              | 2.049445   |
| Access to credit                    | 0.5513591    | 0.6212226                              | 1.73561    |
| Job status of household head        | -0.957421**  | 0.1727676                              | 0.3838816  |
| Perception toward urban agriculture | 1.747034***  | 4.183969                               | 5.73756    |
| Market demand                       | 0.8285042*   | 1.020861                               | 2.289891   |
| Location of the residence           | 0.0505116    | 0.1677241                              | 1.051809   |
| Monthly income of household         | 0-.0002499   | 0.0003077                              | 0.9997501  |
| Training and support                | 0.3492977*** | 0.189215                               | 1.418071   |
| _cons                               | -3.735249    | 0.0461779                              | 0.0238672  |
| Logistic regression                 |              | Observations                           | = 340      |
|                                     |              | chi <sup>2</sup> (13) Prob >           | = 30.14    |
|                                     |              | chi <sup>2</sup> Pseudo R <sup>2</sup> | = 0.0045   |
| Log likelihood = -102.3398          |              |  | = 0.1284   |

Source: survey results 2020/1.

**Impact of urban agriculture on food security**

Adopting urban agriculture on the sample household food security was analyzed using propensity score matching (PSM). While evaluating the impacts using PSM in this study, it was possible to estimate the propensity score, select the matching algorithm, do balance checking of the two groups characteristics, and estimate the impact.

**Propensity score estimation**

With the available literature and considering the fitness for estimating the propensity score, we employed the logit model to estimate propensity scores by carefully considering PSM assumptions. Table 4 shows the propensity score values, which indicate the probability of adopting urban agriculture.

After estimating PS, the common support region for the estimated score was constructed based on



the statistical analysis of adopters and non-adopters of urban agriculture. The common support region was determined by taking the minimum of maximum values and the maximum of minimum values for the propensity scores of the two groups. Thus, the common support region

was between 0.0428562 (the maximum of minimum) and 0.9918891 (the minimum of maximum) value of propensity score (Table 5). Consequently, we excluded 62 observations from the impact analysis due to overlap conditions, comprising 37 adopters and 25 non-adopters.

**Table 4.** Logit model estimation results of propensity score on adoption of urban agriculture.

| Urban agriculture                   | Coefficient | Standard error  | P >  z               |
|-------------------------------------|-------------|---|----------------------|
| Age of household head               | 0.0164665   | 0.0352731   | 0.635                |
| Sex of household head               | -0.2937674  | 0.2946062   | 0.457                |
| Family size                         | 0.3187638   | 0.1629197   | 0.007                |
| Education of household head         | 0.0798305   | 0.076964  | 0.261                |
| Available land for farming          | -0.0518295  | 0.7379808   | 0.947                |
| Homeownership                       | 0.7175692   | 0.8336504   | 0.078                |
| Access to credit                    | 0.5513591   | 0.6212226   | 0.123                |
| Job status of household head        | -0.957421   | 0.1727676   | 0.033                |
| Perception toward urban agriculture | 1.747034    | 4.183969  | 0.017                |
| Market demand                       | 0.8285042   | 1.020861  | 0.063                |
| Location of the residence           | 0.0505116   | 0.1677241   | 0.751                |
| Monthly income of household         | -0.0002499  | 0.0003077   | 0.417                |
| Training and support                | 0.3492977   | 0.189215  | 0.009                |
| _cons                               | -3.735249   | 0.0461779   | 0.054                |
| Logistic regression                 |             | Observations chi <sup>2</sup><br>(13) Prob > chi <sup>2</sup> Pseudo R <sup>2</sup> | = 340<br>= 30.14     |
| Log likelihood = -102.3398          |             |   | = 0.0045<br>= 0.1284 |
| Monthly income of household         | -0.0002499  | 0.0003077   | 0.417                |
| Training and support                | 0.3492977   | 0.189215  | 0.009                |
| _cons                               | -3.735249   | 0.0461779   | 0.054                |
| Logistic regression                 |             | Observations chi <sup>2</sup><br>(13) Prob > chi <sup>2</sup> Pseudo R <sup>2</sup> | = 340<br>= 30.14     |
| Log likelihood = -102.3398          |             |   | = 0.0045<br>= 0.1284 |

Source: survey results 2020/1.

Note: \*\*\* and \*\* represents the significance level (P≤0.05) and (P≤0.01).

**Table 5.** Common support region for estimated propensity scores.

| Variable              |             | Observation | Mean value | Standard deviation | Minimum   | Maximum   |
|-----------------------|-------------|-------------|------------|--------------------|-----------|-----------|
| Propensity score (PS) | Adopter     | 145         | 0.8205488  | 0.2247227          | 0.0428562 | 1         |
|                       | Non-adopter | 133         | 0.2817664  | 0.2689426          | 0.0095714 | 0.9918891 |
|                       | Support     | 278         | 0.5514899  | 0.3336957          | 0.041403  | 0.9918891 |

Source: computation from survey results 2020/1.

After estimating the propensity score, the value of the treated group was matched with the control groups with similar propensity scores to get the effect of the treatment. This was done using the matching algorithm, including nearest neighbor matching, radius matching, and Kebele matching. The mean bias, the number of matched observations, the number of balanced covariates, and the value of the pseudo R square are the main criteria for selecting the best matching algorithm, provided that the better and preferred match becomes the matching algorithm with the lowest mean standardized bias, lowest pseudo R square, approximately equal number of matched

observations, equal number of balanced covariates compared to other matching algorithms, high total bias reduction, and the insignificant p-values of the likelihood ratio test after matching. Thus, the mean bias, the number of matched observations, the number of balanced covariates, and the value of the pseudo R square are estimated (Table 6). Accordingly, the nearest-neighbor matching was optimal, so these appeared essential in matching the units of the treatment (adopters) and controlled group (non-adopters) while applying PSM to estimate the impact of adopting urban agriculture.

**Table 6.** Matching algorithm selection.

| Outcome variables | Matching algorithm | Mean bias  | Pseudo <sub>R</sub> <sup>2</sup> | Number of matched observations | Number of balanced covariate |
|-------------------|--------------------|------------|----------------------------------|--------------------------------|------------------------------|
| Food security     | Nearest neighbor   | <b>4.1</b> | <b>0.092</b>                     | <b>278</b>                     | <b>14</b>                    |
|                   | Radius matching    | 8.2        | 0.094                            | 276                            | 12                           |
|                   | Kebele matching    | 10.6       | 0.124                            | 278                            | 12                           |

The matched units in the adopters and non-adopters are statistically comparable once the units are matched. T-test was used for comparing the means of all covariates, included in the propensity score in determining the similarity of means of the two groups (adopters and non-adopters). The individual covariate mean difference between the two groups is less than 25%, and the overall absolute mean bias (4.1%) is between 2 and 5%.

The overall balancing test indicated no significant difference between the adopters and non-adopters on the covariates after matching because the chi2-test indicates an insignificant difference between them (Table 7).

***Estimation of average treatment effect***

After checking the balance, the average treatment effect was estimated by averaging the differences in outcome between each treatment unit (adoption) and its comparison groups (non-adoption) and interpreted as the impact of urban agriculture adoption on food security. The impact evaluation of the average treatment effect on a treated unit in adopting urban agriculture became possible via the nearest neighbor, and it estimated standard errors for the matching estimator to account for the estimated propensity score. The bootstrapping method with 100 replications appeared feasible (Table 8), showing the impact of urban agriculture adoption on household food security.

**Table 7.** Overall balance indicator of covariates.

|               | Sample    | PsR2   | LR Chi <sup>2</sup> | P > Chi <sup>2</sup> | Mean bias | Medium bias |
|---------------|-----------|--------|---------------------|----------------------|-----------|-------------|
| Food security | Unmatched | 0.4927 | 255.07              | 0.001                | 38.5      | 26.6        |
|               | Matched   | 0.090  | 48.97               | 0.879                | 4.1       | 4.8         |

Source: survey results 2020/1.

**Table 8.** Impact of adopting urban agriculture on household food security.

| Variable      | Sample    | Treated | Controls | Difference | Standard error (bootstrapped) | t-statistics |
|---------------|-----------|---------|----------|------------|-------------------------------|--------------|
| Food security | Unmatched | 0.23    | 0.14     | 0.09       | 0.04                          | 2.25         |
|               | ATT       | 0.60    | 0.02     | 0.58       | 0.07                          | 11.52***     |

Table 8 indicated that the average treatment effect on the treatment group was significant ( $P \leq 0.01$ ). This indicated that the adoption of urban agriculture had an impact on food security. When a farmer adopted urban agriculture, the likelihood of becoming food secure would increase by 0.60, *ceteris paribus*. Ngahdiman et al. (2017) indicated that practicing urban agriculture can build a strong and convincing foundation for Malaysians to minimize the impact

of food scarcity and climate change. The result agrees with the findings of Jaleta et al. (2018). Moreover, the practice of urban agriculture had significant effects on the respondents' livelihood in terms of improvements in the standard of living and saving patterns (Akinagbe & Ipinmoye, 2022). An analysis enabled the checking of the extent to which the study was free from bias resulting from unobserved variable sensitivity (Table 9).

**Table 9.** Result of sensitivity analysis using Rosenbaum bounding approach.

| Outcomes       | $e\gamma = 1$ | $e\gamma = 1.5$ | $e\gamma = 2$ | $e\gamma = 2.5$ |
|----------------|---------------|-----------------|---------------|-----------------|
| Calorie intake | 0.00001       | 0.002177        | 0.042627      | 0.091174        |

The results indicated that the inference for the impact of urban agriculture does not change. The odds of being treated were allowed to differ up to  $e\gamma = 2.5$ , meaning that the outcome variable estimated, at various levels of the critical value of  $e\gamma$ , the p-critical values are significant, which further indicates that the study has considered important covariates that affected both participation and outcome variables. Therefore, it is possible to conclude that impact estimates (ATT) on outcome variables were not sensitive to unobserved selection bias.

**Conclusion**

The study suggested that adoption is related to perception, training, and support. Thus, we highly recommend that town education offices, urban agriculture, and cooperative offices teach these groups via an integrated functional adult education program (training) and support them

in cooperative organizations. Family size encouraged the adoption of urban agriculture, while a good job status of the household head discouraged it. This relationship indicates that urban agriculture can address urban youth unemployment.

Moreover, the adoption of urban agriculture had a positive and significant impact on food security. However, the people in the area are not aware of the effect of urban agriculture on food security and are unfamiliar with the growing market demand. Therefore, the government should engage unemployed people in urban agriculture by providing training to improve their perception and entrepreneurial skills. To make the best decisions possible, urban consumers, especially disadvantaged customers, should be able to make informed decisions about food production, processing, storage, preparation, and distribution. Policymakers need to learn and

inform the benefits of urban agriculture. The requirements and benefits of urban agriculture should receive attention through physical planning, considering land tenure, water availability, and drainage.

This research also suggested the feasibility of inter- and transdisciplinary research strategies and a critical approach to urban agricultural practices. It can involve encouraging practitioner-researcher cooperation and supporting urban farmer efforts to produce safe, nutrient-rich foods for individual consumption and municipal marketplaces. A sustainable assessment of urban agriculture may be a prelude to supporting agriculture in urban and quasi-urban spaces.

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### Conflicts of Interest

The authors indicate no conflict of interest in this work.

### References

- Agren G, Gibson RS. 1969. Food composition table for use in Ethiopia (No. 16). Almövist & Wiksell Bokhandel.
- Ahmed MH, Mesfin HM. 2017. The impact of agricultural cooperatives membership on the wellbeing of smallholder farmers: empirical evidence from eastern Ethiopia. *Agricultural and Food Economics* 5(1), 1-20.
- Ahmed UI, Ying L, Bashir MK, Abid M, Zulfiqar F. 2017. Status and determinants of small farming households' food security and role of market access in enhancing food security in rural Pakistan. *PloS One* 12(10), e0185466.
- Akinngabe OM, Ipinmoye OE. 2022. Urban agriculture practices and households' livelihoods in Ondo State, Nigeria. *Journal of Agricultural Extension* 26(3), 60-73.
- Amare A, Simane B. 2017. Assessment of household food security in the face of climate change and variability in the upper blue-nile of Ethiopia. *Journal of Agricultural Science* 7, 285-300.
- Armar-Klemesu M. 2001. Urban agriculture and food security nutrition and health, thematic paper 4 in N. Bakker et al., growing cities, growing food: urban agriculture on the policy agenda, Fefdafing: DSE.
- Asfaw S, Shiferaw B, Simtowe F, Lipper L. 2012. Impact of modern agricultural technologies on smallholder welfare: evidence from Tanzania and Ethiopia. *Food Policy* 37(3), 283-295.
- Caliendo M, Kopeinig S. 2008. Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys* 22(1), 31-72.
- Cochran, W.G. (1963) *Sampling Techniques*, Wiley, New York.
- Cook JT, Black M, Chilton M, Cutts D, Ettinger de Cuba S, Heeren TC, Frank DA. 2013. Are food insecurity's health impacts underestimated in the US population? Marginal food security also predicts adverse health outcomes in young US children and mothers. *Advances in Nutrition* 4(1), 51-61.
- CSA. 2018. *Population projection of Ethiopia for all regions at Woreda level from 2014–2017*. Ethiopian Population and Housing Census Report.
- Danso-Abbeam G, Bosiako JA, Ehiakpor DS, Mabe FN. 2017. Adoption of improved maize variety among farm households in the northern region of Ghana. *Cogent Economics & Finance* 5(1), 1416896.
- Egal F, Valstar A, Meershoek S. 2001. *Urban Agriculture, Household Food Security and Nutrition in Southern Africa*. Mimeo, FAO: Rome.
- FAO (Food and Agricultural Organization). 2017. 'Global report on food crises'. Food and Agricultural Organization, Rome, Italy.
- FAO (Food and Agriculture Organization of the United Nations). (2019b). *Africa Regional Overview of Food Security and Nutrition Containing the Damage of Economic Slowdowns and Downturns to Food Insecurity in Africa*. Retrieved from <http://www.fao.org/3/ca7343en/CA7343EN.pdf>.
- Gitz V, Meybeck A, Lipper L, Young CD, Braatz S. 2016. Climate change and food security: risks and responses. Food and Agriculture Organization of the United Nations (FAO) Report, 110(2).
- Gore CD. 2018. How African cities lead: urban policy innovation and agriculture in Kampala and Nairobi. *World Development* 108, 169-180.
- Grebitus C, Chenarides L, Muenich R, Mahalov A. 2020. Consumers' perception of urban farming—an exploratory study. *Frontiers in Sustainable Food Systems* 4, 79.
- GZoANRs (Gurage Zone office of Agriculture and Natural Resources). *Annual Report on the Overall Agricultural Statistics and Status of Zonal Agricultural Sector No. 217*. Wolkite, Ethiopia. 2017.
- Hallett S, Hoagland L, Toner E. 2016. Urban agriculture: environmental, economic, and social perspectives. *Horticultural Reviews* 44, 65-120.
- Hayuningtyas M. 2017. "Urban agriculture development: a strategy to support food security" in 2nd International Conference on Sustainable Agriculture and Food Security: a comprehensive approach. *KnE Life Sciences* 701-713. DOI 10.18502/kls.v2i6.1092
- Heckman JJ, Ichimura H, Todd P. 1998. Matching as an econometric evaluation estimator. *The Review of Economic Studies* 65(2), 261-294.
- Ibrahim MK, Haruna M, Shaibu UM. 2020. Analysis of household participation in urban agriculture: empirical

- evidence from urban households in Kogi state, Nigeria. *Asian Journal of Economics, Business and Accounting* 17(1), 23-31.
- Ida Naziera N, Rika T, Zainalabidin M, Sharifuddin J. 2017. Factors affecting urban dwellers to practice urban agriculture. *International Journal of Advanced Research* 5, 1580-1587.
- Jaleta M, Kassie M, Marenaya P, Yirga C, Erenstein O. 2018. Impact of improved maize adoption on household food security of maize producing smallholder farmers in Ethiopia. *Food Security* 10, 81-93.
- Jerzak MA, Śmiglak-Krajewska M. 2020. Globalization of the market for vegetable protein feed and its impact on sustainable agricultural development and food security in EU countries illustrated by the example of Poland. *Sustainability* 12(3), 888.
- Kaliba AR, Mazvimavi K, Gregory TL, Mgonja FM, Mgonja M. 2018. Factors affecting adoption of improved sorghum varieties in Tanzania under information and capital constraints. *Agricultural and Food Economics* 6(1), 1-21.
- Kikulwe EM, Kyanjo JL, Kato E, Ssali RT, Erima R, Mpiira S, Karamura E. 2019. Management of banana xanthomonas wilt: evidence from impact of adoption of cultural control practices in Uganda. *Sustainability* 11(9), 2610.
- Knoema. Retrieved from Ethiopia–Urban population as a share of the total population: [https://knoema.com/atlas/Ethiopia/Urban-population\(2020\)](https://knoema.com/atlas/Ethiopia/Urban-population(2020)). Accessed 24, July 2022.
- Konja DT. 2021. Technology adoption and output difference among groundnut farmers in northern Ghana. *The European Journal of Development Research* 1-18.
- Lamichhane J, Sharma T, Gairhe S, Adhikari SP. 2018. Factors affecting the adoption of improved maize varieties in western hills of Nepal-a tobit model analysis. *Applied Economics & Business* 2(1), 1-11.
- Milkias D, Abdulahi A. 2018. Determinants of agricultural technology adoption: the case of improved highland maize varieties in Toke Kutaye District, Oromia Regional State, Ethiopia. *Journal of Investment and Management* 7(4), 125-132.
- Mohamed AA. 2017. Food security situation in Ethiopia: a review study. *International Journal of Health Economics and Policy* 2(3), 86-96.
- Nations U. 2018. Revision of world urbanization prospects. United Nations: New York, NY, USA, 799.
- Negussie FA. 2020. Impact of row planting teff technology adoption on the income of smallholder farmers: the case of Hidabu Abote District, North Shoa Zone of Oromia Region, Ethiopia. *International Journal of Agricultural Science and Food Technology* 6(2), 195-203.
- Ngahdiman Ida N. 2017. *Intention to practice agriculture among urban dwellers in the Klang Valley Malaysia*. Master's Thesis, Universiti Putra Malaysia.
- Palanivel T. 2017. Rapid urbanisation: opportunities and challenges to improve the well-being of societies. United Nation Development Programme.
- Rosenbaum PR, Rosenbaum PR. 2002. Overt Bias in Observational Studies 71-104. Springer, New York.
- Shinbrot XA, Jones KW, Rivera-Castañeda A, López-Báez W, Ojima DS. 2019. Smallholder farmer adoption of climate-related adaptation strategies: the importance of vulnerability context, livelihood assets, and climate perceptions. *Environmental Management* 63, 583-595.
- Sibhatu KT, Qaim M. 2017. Rural food security, subsistence agriculture, and seasonality. *PloS One* 12(10), e0186406.
- Sraboni E, Malapit HJ, Quisumbing AR, Ahmed AU. 2014. Women's empowerment in agriculture: what role for food security in Bangladesh? *World Development* 61, 11-52.
- Tefera MM. 2010. Food security attainment role of urban agriculture: a case study from Adama town, central Ethiopia. *Journal of Sustainable Development in Africa* 12(3), 223-249.
- United Nations Population Fund. 2020. World urbanization prospects: the 2019 revision. <http://esa.un.org/unpd/wup/CD-ROM/Default.aspx>. Accessed 29, January 2022.
- van Lier LE, Utter J, Denny S, Lucassen M, Dyson B, Clark T. 2017. Home gardening and the health and well-being of adolescents. *Health Promotion Practice* 18(1), 34-43.
- Walljasper C, Polansek T. 2020. Home gardening blooms around the world during coronavirus lockdowns. Reuters. Available online at: <https://www.reuters.com/article/us-health-coronavirus-gardens/home-gardeningblooms-around-the-world-during-coronavirus-lockdowns-idUSKBN2220D3>.
- Yalew A. 2020. Urban agriculture in Ethiopia: an overview. *Regional Economic Development Research* 1(2), 85-92. doi.org/10.37256/redr.122020607.