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**Abstract:** Technologies-based production practices are critical for agricultural growth and sustainable development in low-income countries like Nepal. In the last few years, tunnel house has been increasingly promoted as tools to enhance smallholder farmers' livelihood and tackle climate adversaries. However, little is known about what factor determines its adoption and whether it helps smallholders adapt to climate change and experience better livelihood. We address these gaps using the cross-sectional survey data collected from 62 adopters and 92 non-adopters in three municipalities of Bagmati Province. We employed descriptive analysis and probit model and found out that age, farm size, and ethnicity strongly influence the technology adoption amongst smallholder farmers. Additionally, treatment model and ordinary least square (OLS) regression were utilized to examine tunnel technology's effect. Our study shows that tunnel significantly increases production by 32 tons/year/hectare and protects crops from climate change effects such as heavy rainfall and temperature change. Likewise, tunnel technology increases the net crop income by $1700/year/hectare. However, the economic benefit is not substantial compared to technology's adoption cost as adopters incur enormous costs of $12,000/year/hectare on equipment, labor and resources. These results suggest policymakers should concentrate on reducing the technology's cost, which could be achieved through subsidies, financial support, or price control mechanisms. Ensuring technology's affordability can contribute to smallholder farmers' sustainable livelihood in Nepal and countries with similar contexts.

**Keywords:** livelihood; smallholder farmers; tunnel technology; sustainable development; agricultural growth



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## 1. Introduction

Poverty alleviation has been a priority for the last few decades, including the recently instituted sustainable development goals (SDGs). The SDGs are a combination of 17 goals designed by the United Nations to be a blueprint for achieving a better and more sustainable future for all by 2030 [1]. Particularly, SDG 1, "end poverty in all forms everywhere", SDG 2, "end hunger, achieve food security and improved nutrition and promote sustainable agriculture", and SDG 13, "take urgent action to combat climate change and its impacts" deal with poverty alleviation and sustainable development of the poor population. However, 1.4 billion people still live below the poverty line of less than USD 1.90 a day. Amongst these, 767 million (55%) are smallholder farmers [2], and more than

84% of them have a farm size of less than 2 hectares [3]. Smallholder farmers are also more vulnerable to climate change as they lack adequate resources to tackle its adverse effect [4]. Therefore, identifying sustainable strategies to improve smallholder farmers' living conditions can contribute to economic growth, reduce global poverty and achieve sustainable development goals [5].

Adoption of environment-friendly technology can enhance farmers' ability to tackle climate change effects, boost productivity, raise producers' incomes, and contribute to household welfare [6,7]. Several developing countries have emphasized climate-smart agriculture technology as interventions to improve smallholder farmers' living conditions. For instance, Singh et al. [8] showed that integrated weed management technology increased crop yield and contributed to climate-resilient livelihood. Gebbers and Adamchuk [9] illustrated that precision agriculture ensures food security maintaining the environment quality. Likewise, [10] demonstrated farm management practice increased the rice yield while protecting crops from natural disasters.

Nepal is a poor agricultural country in South Asia, where the government has emphasized technology-led interventions as strategies for the growth and development of farmers, the majority of whom are smallholders [11]. Since the earliest attempt of agricultural interventions through the construction of an irrigation canal in Saptari and an experimental farm in Kathmandu in 1923 [12], the government has highlighted technology-led intervention in its strategic plans, policies, and extension services [13]. In recent times, the government has acknowledged the climate change risks and highlighted the promotion of climate-smart agriculture technologies. One such widely promoted technology is tunnel house for smallholder vegetable farmers. Numerous government projects have promoted tunnel technology-based protected cultivation in many hectares of land [14,15]. For instance, the government constructed 10 high-tech greenhouses and 86 semi high-tech greenhouses through Prime Minister Agriculture Modernization Project (PMAMP) in the last couple of years. Likewise, various national and international development organizations have implemented several projects where tunnel technology has remained as one of the essential components. Thus, there has been a substantial increase in the number of smallholder farmers adopting tunnel technology over the last decade [16,17]. As reported by [14], Kathmandu alone covered 250 hectares of land area under the tunnel farming system in 2015–2016.

Despite higher promotion and adoption, little is known about whether the technology has been beneficial for smallholder farmers. Few previous studies have attempted to examine the technology's benefits through the cost–benefit ratio, and net return measures in Nepal [18], India [19,20], and Pakistan [21,22]. However, such measures do not give accurate estimates as they do not consider the structural differences of tunnel adopters and non-adopters. Several factors may influence the farmers' adoption/non-adoption behavior, which leads to the self-selection bias and endogeneity problem. Likewise, there is no evidence of whether the technology has been efficient in tackling the climate change risk experienced by smallholder farmers. There is a lack of research that has comprehensibly examined the effect of tunnel technology combining social, economic, and environmental components.

This study aims to address these gaps. The research aims to examine what socio-factors influence households' technology adoption decisions and whether technology adoption contributes to their wellbeing. We concentrate mainly on micro-level household socio-economic factors to measure these effects. We use descriptive analysis and probit regression model to examine if adopters and non-adopters differ in their characteristics. This helps in identifying the determinants for tunnel technology adoption. We then employ the treatment model to examine whether tunnel technology is beneficial for smallholder farmers. The treatment model here controls the aforementioned structural differences between adopters and non-adopters, along with the endogeneity problem. The beneficial impacts of tunnel technology are measured in terms of crop productivity and net crop income. The treatment model results are also compared with OLS models to check if tunnel technology's impact significantly differs when structural differences between adopters and non-adopters are controlled.

The findings of the research contribute to knowledge in three ways. First, we attempt to cover the gap in the existing literature on tunnel technology adoption. Second, we intend to provide empirical evidence on tunnel technology's appropriateness for smallholder farmers' sustainable livelihood. This will further indicate whether the tunnel technology should be replicated and promoted amongst other farmers in Nepal and other similar countries. Third, we seek to influence policymakers to formulate poverty alleviation strategies for farmers based on agricultural technology intervention such as tunnel farming.

*Tunnel House Technology in Nepal*

Tunnel house is an infrastructure-based technology that facilitates crop production for an extended period [23]. Although the developed countries introduced tunnel technology a long time ago, it is comparatively new to Nepal. Kafle and Shrestha [24] reported it was first introduced in 1996 by the Regional Agriculture Research Station—Lumle. In contrast to the sophisticated tunnel technology in practice in developed countries, Nepalese farmers have adopted it in a simpler form [23]. The tunnel structure generally consists of bamboos or galvanized iron (GI) pipe framework, covered with transparent silpaulin plastic, usually 45 to 90 GSM. The plastic is overlaid only at the top of the gabled roof in the hilly region, but the tunnel structure is fully covered in the cooler region. The recommended dimension is 12 to 25 m length, 5 to 6 m width, and 2 to 4 m height based on the area's elevation [25]. The walking path inside the tunnel is recommended at least 75 cm. However, the Nepalese farmers often resize the tunnel area based on their farm's size and shape. Most tunnel growers use mulching plastic film and equip their tunnels with drip irrigation [23,25]. Moreover, they apply chemicals (fertilizer, insecticides, herbicides, and fungicides) in a controlled and optimum way to maximize soil fertility and produce high-quality vegetables. Our study considered the Ministry of Agriculture's recommended [25] semi-closed tunnel consisting of bamboo pipe structure with a gabled roof of 80–90 GSM plastic and equipped with drip irrigation, as shown in Figure 1. The tunnel had a walking path of 75 cm.

**Figure 1.** Tunnel technology-based farming system.

## 2. Materials and Methods

### 2.1. Data

The study used data from the primary household survey conducted in December 2019. Three municipalities, namely, Tokha, Mahalaxmi, and Suryabinayak of Bagmati province, were purposively selected as many tunnel farmers were present in these regions. The sample for tunnel adopters and non-adopters was selected from the data record of a local government institution—the Agriculture Knowledge Center, Lalitpur, Nepal. We surveyed 154 households: 62 were tunnel adopters and 92 were non-adopters. For the selection of adopters, we utilised two criteria. First, farms must be smaller than 1 hectare (ha) because most farmers in Nepal are smallholders [26]. Second, crops grown inside the tunnel must cover 80% to 90% of their farmland This was to measure tunnel technology's actual impact, which was not possible if we selected farmers adopting tunnel technology in a small portion of their land. As most farmers were practicing tunnels in 20–30% of their farms, we found 223 households met these criteria and are suitable for our study. We randomly selected 30% of eligible adopters as samples for our study. Interestingly, we also found that all farmers switched to tomatoes after adopting tunnel technology. Tomatoes have higher demand and better market certainty because they are consumed daily in the form of vegetable seasoning or pickles.

Likewise, for non-adopters, we considered households having a farm size of less than 1 ha, who did not have any tunnel houses on their farm. Notably, we found that most non-adopters were growing multiple vegetable crops. We screened for farmers cultivating only a single vegetable crop as it is challenging to collect the actual data for multiple vegetable crops, given that each crop varies in its cropping cycles. We selected potatoes growers as non-adopters as they were the only farmers who were growing a single crop for the entire year. Furthermore, farmers potatoes production decision was also led by market demand and market certainty as potato is also consumed daily as a primary vegetable. This way, we found a comparable group of farmers similar to tomato growers in important aspects, such as production decision and farm size, but different in technology adoption. We found 300 potatoes grower as suitable non-adopters in three study areas. In total, 30% of total eligible households were selected randomly as samples for the study.

The household survey was carried out using a semi-structured questionnaire. The questions were developed after reviewing relevant literature on technology adoption [6,27–29]. Next, we documented possible variables on cost activities, returns and issues of tunnel farming. Then we conducted informant interviews with experts and focus group discussions with farmers to check if we captured all cost, benefit items and potential issues. Additionally, we also asked questions regarding how tunnel technology has helped farmers adapt to climate change impacts. Finally, we refined all the variables to form a semi-structured questionnaire to collect detailed information from farmers. The questions were divided into three parts. The first part had questions on socio-demographic characteristics such as farmers' age, gender, family size, the active and dependent population in the family, ethnicity, and educational status. The second part asked questions about economic and farm characteristics related to farm size, household income, farming experience, farm income, and the distance between the farm and the nearest wholesale market.

In the third part, questions related to production cost, crop production, and income were included. The production cost is composed of the cost incurred on inputs (seeds, fertilizers, pesticides, irrigation, tools, utilities), labor, and land. Additionally, farmers adopting tunnels were also asked about the initial investment they spent to purchase all the essential components and install the tunnel house (drip irrigation installation, plastic mulching, and the bamboo/metal pipes structures). However, since the tunnel is assumed to have a life span of three years, one-third of the total initial investment (minus depreciation cost) was only included as the annual cost for further statistical analysis. Notably, during a preliminary discussion with the farmers' group, we learned that tunnel adopters grow tomatoes for one cropping cycle that lasts for 9 to 10 months. In contrast, non-adopters grow potatoes for two cropping cycles, each lasting 4 to 5 months with a month gap between two subsequent cycles. Therefore, we collected all the information on cost, income, and production for one cropping cycle for tomatoes and two cropping cycles for potatoes to reduce the difference in profitability and risk level and to ensure the comparison and statistical analysis was done on common ground using annual values.

*2.2. Econometric Framework*

The adoption of tunnel technology can be modelled using a random utility framework [6,27,30]. The random utility framework states that a rational farm household, $i$, chooses tunnel technology which maximizes their utility. Thus, a rational farmer always wants to adopt tunnel technology until the utility accrued from adoption $(U_{iA})$ is greater than the utility derived from non-adoption $(U_N)$. It can be mathematically denoted by,

$$T^*{}_{\text{i}} = U_{iA} - U_{iN} > 0$$

where $T^*$ is the difference between the utilities derived from the technology adoption and non-adoption.

Since these utilities are unobservable, they can be expressed as a function of observable elements in the following latent variable model;

$$T^*{}_i = \beta Z_i + \mathrm{e}_i, \text{ with } T^*{}_i = \begin{cases} 1\ if\ T^*{}_i > 0 \\ 0\ otherwise \end{cases}. \tag{1}$$

$T$ is a binary dummy variable with a value of 1 for the adoption of tunnel technology and 0 otherwise; $\beta$ represents the vector of parameters to be estimated; $Z$ is a vector of explanatory variables, and $e$ is the error term.

Kassie et al. [30], Khonje et al. [27], and Tufa et al. [7] showed the effect of technology adoption on net crop income, yield, and poverty rate. Following them, we used crop productivity and net crop income as outcome variables to examine tunnel technology's impact on profitability. Assuming that the increase in productivity and net crop income is a linear function of a binary dummy variable for tunnel adoption ($T_i$) and a vector of other explanatory variables ($X_i$), the linear regression equation can be represented by the following equation:

$$Y_i = \beta_1 T_i + \beta_2 X_i + \mu_i \tag{2}$$

where $Y_i$ denotes outcome variables (crop productivity or the net income), $\beta_1$ and $\beta_2$ denotes the vector of parameters to be estimated, and $\mu_i$ is an error term. $\beta_1$ specifically gives estimation for crop productivity and net crop income due to the adoption of tunnel technology. However, for $\beta_1$ to accurately measure the impact of tunnel technology adoption on crop productivity and net crop income, farmers should be randomly assigned to adoption or non-adoption groups [30,31]. Since farmers themselves decide whether to adopt tunnel technology, this decision is likely to influence individual and household characteristics (observable and unobservable) that may be correlated to the outcome variable. Thus, dummy variable $T$ representing tunnel technology adoption cannot be treated as an exogenous variable. The estimation of parameters using ordinary least square (OLS) in Equation (2) may be inconsistent and produces biased results leading to endogeneity.

Upon endogeneity in the technology adoption variable, it is vital to use an appropriate method to correct it. One possible way with cross-section data is to use propensity score matching (PSM), which can control bias caused by observable characteristics [27]. However, PSM does not account for other unobservable factors that might affect technology adoption. The treatment model could be appropriate in such contexts as they account for both observed and unobserved characteristics through instrumental variables [32]. The treatment model requires identifying appropriate instruments that should correlate with tunnel adoption but do not influence the outcome variables other than through the tunnel adoption. Moreover, a good instrument must be uncorrelated with the error term. If $z$ is a vector of instrumental variables, then it should be:

i. Correlated with $T$: $cov\ (z, T) \neq 0$;
ii. Uncorrelated with $\mu$: $cov\ (z, \mu) = 0$.

Finding appropriate instruments is, however, a difficult task. Previous research has used variables like education, risk perceptions, neighbours' influence, distance to the nearest market, paved road or the nearest extension office, credit access/constraints, and information access as instruments [28,33–35]. Among these we found two instruments appropriate to our situation: (i) the influence of neighbours' farming practice and (ii) distance to the nearest agrovet. We verified these instruments with the expert to confirm they are applicable in our situation. Likewise, we also checked the instrument with farmers during a preliminary group discussion. Many farmers revealed that they closely observe neighbours' agricultural practices before deciding any farming practices or technology adoption during group discussion; but their neighbours' farming practices do not have any impact on their production or income. Likewise, when an agrovet is nearby, farmers frequently visit the agrovets, which helps them learn about the latest farming practices and technologies such as tunnel technology. Thus, they are more likely to adopt new technology; however, closeness to agrovets does not affect their income or crop productivity.

With the identification of instrumental variables, the estimation of outcome variables ($Y$) due to technology adoption ($T$) is carried out in two stages. In the first stage, the technology adoption is regressed on the instrument '$z$' and other exogenous variables ($X$) to isolate the part of the treatment variable independent of other unobserved characteristics affecting the outcome variable as shown in Equation (3). Like previous researches from Kabunga et al. [33], Kassie et al. [30] and Kumar et al. [28], we used age, gender, family size, ethnicity, area cultivated, the total dependent and economically active member in the family as exogenous variables for explaining the tunnel adoption.

$$T_i \; = \; \alpha_1 z_i + \alpha_2 X_i + €_i \tag{3}$$

The predicted $T_i$ hat from this regression reflects the part of the technology adoption affected only by $z$ and embodies only exogenous variation in the technology adoption. Then, in the second stage, the outcome variable regresses on the predicted value of technology adoption $T_i$ *hat* and other exogenous variables, as shown in Equation (4) below:

$$Y_i \; = \; \alpha + \beta_1 T_i hat + \beta_2 X_i + \mu_i \tag{4}$$

Through instrumenting, technology adoption is assumed to be free from its correlation with the error term. If the assumptions $cov\ (z, T) \neq 0$ and $cov\ (z, \mu) = 0$ hold, IV consistently identifies the tunnel adoption's mean impact attributable to the instrumental variables. However, before concluding that IV produced biased-free estimates, it is critical to check whether selection bias or endogeneity existed. It can be tested statistically using instrumental variables through the Durbin–Wu–Hausman test.

In the Durbin–Wu–Hausman test, the technology adoption variable ($T_i$) is regressed on the instrumental variables ($z$) and other exogenous variables $X$, as shown in Equation (5) below.

$$T_i \; = \; \pi_0 X_i + \pi_1 z_i + \varepsilon \tag{5}$$

Then predicted residual hat ($\varepsilon hat$) is obtained. These residuals reflect all unobserved heterogeneity affecting treatment not captured by the model's instruments and exogenous variables. Then outcome variable $Y$ is regressed on all the exogenous and predicted error terms, as shown in Equation (6).

$$Y_i \; = \; \beta_1 T_i + \beta_2 X_i + þ\varepsilon_i hat + \mu \tag{6}$$

If the predicted variable $\varepsilon hat$ appears significant through $t$-test on regression output, it indicates that tunnel adoption is endogenous. It further confirms that the treatment model is better suited for the estimation. Otherwise, the $T$ is exogenous, and OLS is preferable over the treatment model. In this study, we compare ordinary OLS and treatment models' results and use the Durbin–Wu–Hausman test to identify a preferable model.

## 3. Results and Discussion

### *3.1. Comparison of the Adopters and Non-Adopters*

The descriptive analysis based on mean difference and *t*-statistics showcasing characteristics of adopters and non-adopters is shown in Table 1. The findings of econometric analysis based on a probit model are shown in Table 2. The findings from both the analysis are similar and align with each other. For instance, the probit model showed that the younger the farmer, the higher the tendency to adopt tunnel technology. The descriptive analysis showed that the tunnel adopters' average age was 37 years younger than non-adopters by five years ($p = 0.001$). This could be because younger farmers are better educated, energetic, risk-takers, and open to new ideas. They are also good at networking and approaching people, which helps access appropriate information and the required resources from supply chain actors, government, and donors. This result aligns with the findings from Nigeria [36] and Moldova [29], where young farmers were adopting more new technologies than older farmers.

**Table 1.** Descriptive statistics of tunnel adopters and non-adopters.

| Variable | Description of Variable | Full Sample | Non-Adopters (NA) | Tunnel Adopters (A) | Difference (A-NA) |
|---|---|---|---|---|---|
| N | Number of Respondents | 154 | 92 | 62 | |
| | | Socio-demographic | | | |
| Age | Age of respondent (years) | 39.62 | 41.48 | 36.68 | −4.80 *** |
| Gender | Gender of the farmer working most of the time in the farm (1 = male; 0 = female) | | | | |
| Female | Respondent is female (%) | 0.17 | 0.2 | 0.14 | −0.06 |
| Male | Respondent is male | 0.33 | 0.4 | 0.27 | −0.13 |
| Household size | Numbers of members in the household | 5.63 | 5.51 | 5.81 | 0.3 |
| Active members | Number of members of the working-age group (15–59 years) | 3.88 | 3.87 | 3.89 | 0.02 |
| Dependent members | Number of members of age groups below 15 and above 59 years | 1.78 | 1.64 | 1.92 | 0.28 |
| Ethnicity | Ethnic background of the respondent | | | | 0 |
| Dalit | Respondent is from Dalit ethnic community (1 = Dalit; 0 = others) | 0.06 | 0.09 | 0.03 | −0.06 * |
| Indigenous | Respondent is from indigenous community (1 = indigenous; 0 = others) | 0.19 | 0.19 | 0.19 | −0.01 * |
| Higher caste | Respondent is from Brahmin and Chettri community (1 = higher caste; 0 = other) | 0.25 | 0.31 | 0.19 | −0.12 |
| Educational status | Education level measured in years of schooling | | | | |
| Unschooled | Respondent with no formal schooling (%) | 0.06 | 0.11 | 0 | −0.11 *** |
| Secondary level | Respondent with 12 or less years of schooling (%) | 0.32 | 0.34 | 0.31 | −0.03 ** |
| Intermediate | Responded with more than 12 years of formal education (%) | 0.12 | 0.15 | 0.1 | −0.05 |
| | | Economic variables | | | |
| Farm size | Area of land under vegetable cultivation measured in hectare (ha) | | 0.226 | 0.373 | 0.15 *** |

**Table 1.** *Cont.*

| Variable | Description of Variable | Full Sample | Non-Adopters (NA) | Tunnel Adopters (A) | Difference (A-NA) |
|---|---|---|---|---|---|
| Cost per ha | Cost of production of vegetables in 1 ha of land (USD/ha) | 11,441.86 | 5606.31 | 17,277.41 | 11,671.10 *** |
| Crop productivity | Total quantity of vegetables produced in 1 ha of land (Ton/ha) | 34.92 | 19.73 | 50.11 | 30.38 *** |
| Income per ha | Total income from vegetable in 1 ha of land (USD/ha) | 15,355.82 | 8233.6 | 22,478.05 | 14,244.44 *** |
| Net crop income per ha | Profit from vegetables in 1 ha of land (USD/ha) | 3913.96 | 2627.29 | 5200.63 | 2573.34 ** |
| Neighbours' influence | Influence of neighbours' farming practices on adoption of tunnel technology (1 = yes; 0 = otherwise) | 0.33 | 0.35 | 0.32 | −0.03 ** |
| Distance to nearest agrovet | Distance between the farm gate and nearest agrovet (km) | 13.06 | 15.53 | 9.4 | −6.13 ** |

***, **, * are significant at 1%, 5%, and 10% level, respectively.

**Table 2.** Result of probit regression showing determinants of tunnel adoption.

| Variable | Coefficient |
|---|---|
| Age | −0.057 *** (0.019) |
| Gender | −0.340 (0.304) |
| Active members | 0.086 (0.116) |
| Dependent members | 0.094 (0.120) |
| Dalit | −1.494 *** (0.572) |
| Indigenous | 0.431 (0.311) |
| Educational status | 0.946 *** (0.324) |
| Farm size | 2.919 *** (0.808) |
| Neighbours' influence | 2.319 *** (0.678) |
| Distance to nearest agrovet | −0.159 *** (0.033) |
| Constant | −0.967 (1.504) |
| Number of observations | 154 |
| Mean dependent var | 0.403 |
| SD dependent var | 0.492 |
| Pseudo r-squared | 0.479 |
| $\chi^2$ | 99.449 |
| Akaike crit. (AIC) | 130.159 |
| Bayesian crit. (BIC) | 163.565 |

*** is significant at 1% level. Figures in parentheses are robust standard errors.

Likewise, the ethnicity of the farmers significantly affects the adoption of tunnel technology. Farmers from Dalit and Indigenous ethnic groups are less likely to adopt tunnel technology (Table 1). Dalit and indigenous groups are the so-called lower caste people who are usually poor and lack sufficient financial resources to adopt tunnel technology. In their recent studies in Nepal, [28,37] highlighted a similar concern that Dalit has comparatively minimum adoption percentage of improved crop practices and mini tiller technology than other ethnic groups. In terms of education, the years of schooling significantly affect tunnel technology adoption, as shown in Tables 1 and 2. It is interesting to note that all farmers adopting tunnel technology have attained at least a few years of formal education. It may be because of the educated people's motivation and knowledge to adopt new technologies and practices. On the contrary, some non-adopters were uneducated (11%) and did not attend any school (Table 1). This finding coincides with another research in Pakistan, where [38] found out that educated farmers were more likely to adopt new farm technologies.

Neighbours' farming practices and distance to nearest agrovet, which were identified as instrumental variables during group discussion, also significantly influenced tunnel adoption (Table 2). Nearly 68% of the total respondents were influenced by their neighbours' farming practices (Table 1). Most farmers replicate their neighbours' farming techniques and practices to minimize the risk of loss by gaining insights into technical and financial requirements and knowing whether investing in the technology would be profitable. Studies conducted in Ethiopia [34] and India [39] have stated the importance of neighbours in the diffusion and adoption of technology. On the contrary, distance to the nearest agrovet has a significant negative association with technology adoption. The average distance from the tunnel farm to the nearest agrovet is 9.40 km, which is 6 km shorter than non-adopters. As agrovets are essential sources of agricultural information [40], farmers near agrovets are aware of the input markets and technologies and are more likely to adopt technology like tunnel houses. A similar result was reported by Paudel et al. [37] in Nepal as farmers adopted mini tillers when they were close to agrovets.

The economic aspects of tunnel adoption and non-adoption are also assessed. Farmers having larger farm size are more likely to adopt tunnel technology (Table 2). The average farm size of non-adopters and adopters is 0.22 ha and 0.37 ha, respectively (Table 1). In general, larger farms generate a more marketable surplus and have their investment capacity to afford new technologies and take a higher risk than small-scale farms. They can benefit from the economies of scale by introducing appropriate technologies to lower the cost per unit production and increase production. A similar association between technology adoption and farm size was observed in Nepal and Ghana [41,42] and Ghana [42], as farmers with larger farm sizes were more likely to adopt new technologies

The descriptive statistics indicate that productivity and net income per ha are two to three times higher for the tunnel adopters (Table 1). Notably, the cost associated with tunnel technology is also nearly three times higher than open-field cultivation. However, deriving conclusions about the impact from the simple comparison of the mean differences and *t*-statistics could be misleading. Given the significant heterogeneities between adopters and non-adopters, technology adoption is rather endogenous affected by various observable and unobservable factors. Thus, it is necessary to control for these differences between adopters and non-adopters. In the next section, we control for both observable and unobservable differences using the treatment model through instrumental variables. We use neighbours' farming experience and distance to nearest agrovets as instruments. Both instrument variables have a significant association with the technology adoption (Table 2), indicating that they could be suitable instruments to control endogeneity and produce accurate tunnel technology impacts on crop productivity and net crop income. It is important to note that several other unobservable factors, such as price signal, raw materials availability, infrastructure, and government policy, could have affected the farmers' decision to adopt tunnel technology. However, we only considered socio-economic characteristics as determinants and thus observed the differences between adopters and non-adopters concentrating on micro-level household characteristics.

### *3.2. Impact of Tunnel Adoption on Crop Productivity*

The treatment model results showing the impact of tunnel adoption on crop productivity are given in Table 3. For comparison, estimates from ordinary least square models are also added in the third column. The first stage equation, which predicts tunnel technology adoption, gives results quite similar to those of the probit model presented in Table 2. The second stage regression model, which predicts crop productivity, is very similar to the OLS model. Both models show that tunnel technology significantly increases the annual crop productivity by 25 ton/ha and 32 ton/ha, respectively. This finding resembles the outcome of other research in Nepal [26] and Kenya [43], where technology adoption has significantly increased the crop's yield. Notably, the treatment model suggests that crop productivity may be even higher when observable and unobservable differences are controlled using instrumental variables. It further indicates that OLS may underestimate the effect of tunnel technology. Therefore, to confirm this, Wu–Hausman and Durbin chi-square scores are calculated at the bottom of Table 3. The fact that both these scores are significant ($p < 0.01$) implies a selection bias. Thus, it is necessary to estimate crop productivity using the treatment model instead of the OLS model. A similar outcome was also observed by [33] in

Kenya. They also found out that the OLS model underestimated tissue culture's effect on income and hence used the treatment model. Nevertheless, whatever the model is, it is reassuring to learn that tunnel technology significantly increases crop productivity.

**Table 3.** Estimated impact of tunnel farming on crop productivity (ton per hectare).

| Variable | Treatment Model | | OLS |
|---|---|---|---|
| | First Stage | Second Stage | |
| Adoption of tunnel technology | | 32.989 *** (1.634) | 25.717 *** (1.363) |
| Age | −0.046 ** (0.018) | 0.033 (0.064) | −0.030 (0.059) |
| Gender | −0.296 (0.303) | 0.139 (1.173) | −0.378 (1.105) |
| Household size | 0.063 (0.112) | −0.188 (0.444) | |
| Active members | | | −0.238 (0.415) |
| Dependent members | 0.052 (0.131) | −0.202 (0.538) | −0.277 (0.407) |
| Dalit | −1.750 *** (0.597) | 0.908 (1.800) | −1.513 (1.687) |
| Indigenous | 0.389 (0.305) | −2.526048 | −1.457 (1.093) |
| Educational status | 0.921 *** (0.320) | −0.121 (0.536) | −0.432 (0.564) |
| Farm size | 2.931 *** (0.771) | 7.980 *** (2.760) | 14.094 *** (2.597) |
| Neighbours' influence | 2.148 *** (0.658) | | 0.481 (1.234) |
| Distance to nearest agrovet | −0.163 *** (0.029) | | −0.456 *** (0.097) |
| Constant | −1.082 (1.402) | 17.392 *** (3.690) | 27.611 *** (4.019) |
| ath ($\rho$) | | −0.671 *** (0.207) | |
| ln ($\sigma$) | | 1.890 *** (0.063) | |
| N | | 154 | 154 |
| Wald $\chi^2$/F-statistic | | 655.38 | 85.876 |
| Log-likelihood | | −552.402 | |
| R-squared | | | 0.869 |
| LR test of independent equations (Prob > $\chi^2$) | | 0 | |
| Durbin (score) $\chi^2$ | | 18.834 *** | |
| Wu–Hausman F score | | 19.926 *** | |

***, ** are significant at 1% and 5% level, respectively. Figures in parentheses are robust standard errors.

Tunnel technology contributes to crop productivity in several ways. First, the tunnel house protects crops from climate change effects like heavy rainfall and temperature as opposed to crops cultivated in an open field. Second, adopting the tunnel helps efficient use of scarce resources such as water, fertilizers, pesticides, and labour. Usually, tunnels are fitted with drip irrigation structures helping for efficient use of water during water shortage and dry seasons. Likewise, chemicals are also applied in a controlled way that maintain soil fertility and increase crop productivity. Third, tunnel technology prolongs production and allows farmers to grow and harvest the crops continuously, which significantly increases productivity. For instance, farmers could continuously grow tomatoes for 10 to 12 months using tunnel technology, which was impossible if cultivated in open farms. They are more likely to be affected by heavy rainfall and cold temperature/fog during the monsoon and winter seasons. Similar findings were observed in Bangladesh [44], and Malawi [7], where the adoption of improved crop varieties and related technologies increased productivity. Likewise, we also found that climate-smart farming technologies helped farmers adapt to climate-related adversaries contributing to better crop productivity and farm returns [38].

The OLS and treatment models' estimates illustrate that crop productivity is also affected by two other factors. First, farm size has a positive and significant effect on productivity. On the contrary, the farmers from Dalit ethnic group have lower crop productivity than the higher caste group. They are financially destitute and cannot afford to invest in advanced technologies such as tunnel technology, reducing productivity. Paudel et al. [37] reported a similar outcome as Dalit could not produce a large quantity of crops than other higher castes.

### 3.3. Impact on Net Crop Income

Similar to productivity estimates, the results of both OLS and treatment models showcasing impacts on net crop income are presented in Table 4. Likewise, the Wu–Hausman and Durbin chi-square scores are also included in the table. Both scores being significant ($p \leq 0.05$) implies a selection bias, and hence, the treatment model is more appropriate than OLS for predicting net crop income. The treatment and OLS models predict that tunnel technology increases the annual net crop income by $1700 and $2400, respectively, in one hectare of land. These estimates have two important implications. First, the net income gain after technology adoption is not as large compared to the cost associated with its adoption. The farmers must invest nearly $12,000 annually per ha when adopting tunnel technology (Table 1), which is drastically larger than their net crop income (Table 4). This could be because farmers need to invest considerable upfront cost on materials, maintenance and labour than farming in the open field. For instance, tunnel technology requires material such as GI pipes/bamboo, plastic sheets, and strings, which require additional investment, further increasing the cost. Second, the treatment model's estimation indicates that the adopter's net income gain is even lower when selection bias is controlled using instrumental variables. It raises a crucial concern if tunnel technology is economically beneficial for smallholder farmers, given the cost, time, and effort. Similar circumstances were also observed by Miyata et al. [45] in China. They found no significant gain in the farmers' net income when selection bias was controlled through the treatment model.

**Table 4.** Estimated impact of tunnel farming on net crop income (USD per hectare).

| Variable | Treatment Model | | OLS |
|---|---|---|---|
| | First Stage | Second Stage | |
| Adoption of tunnel technology | | 1746.252 *** (386.138) | 2448.086 *** (258.463) |
| Age | −0.056 *** (0.019) | −9.794 (11.910) | −6.241 (11.275) |
| Gender | −0.276 (0.310) | −74,032.52 | −73,706.38 |
| Household size | 0.054 (0.119) | −10,656.26 | |
| Active members | | | −116.326 (78.633) |
| Dependent members | 0.019 (0.135) | −22.911 (96.671) | −10,729.1 |
| Dalit | −1.490 *** (0.562) | −648.452 ** (328.949) | −369.690 (319.783) |
| Indigenous | 0.407 (0.309) | −3.560 (212.643) | −61.703 (207.193) |
| Educational status | 0.736 ** (0.372) | −17,068.11 | −38.211 (106.829) |
| Farm size | 2.785 *** (0.779) | 3853.835 *** (521.072) | 3161.127 *** (492.295) |
| Neighbours' influence | 1.922 ** (0.768) | | 349.721 (233.887) |
| Distance to nearest agrovet | −0.162 *** (0.032) | | 68.329 *** (18.327) |
| Constant | −0.039 (1.672) | 691.860 *** (673.998) | 984.956 ** (761.838) |
| ath ($\rho$) | | 0.291 ** (0.261) | |
| ln ($\sigma$) | | 7.081 *** (0.060) | |
| N | | 154 | 154 |
| Wald $\chi^2$/F-statistic | | 171.24 | 23.982 |
| Log-likelihood | | −1361.2 | |
| R-squared | | | 0.65 |
| LR test of independent equations (Prob > $\chi^2$) | | 0 | |
| Durbin (score) $\chi^2$ | | 6.059 ** | |
| Wu–Hausman F score | | 5.856 ** | |

***, ** are significant at 1% and 5% level, respectively. Figures in parentheses are robust standard errors.

Although not substantial, both OLS and treatment models confirm that farmers can earn additional income from tunnel technology adoption. Other research aligns with our study's findings. For instance, [26,28] showed that the adoption of various improved technologies increased the net farm revenue. Likewise, [30] showed that the adoption of improved groundnut varieties increased the net farm household income. The income gain amongst the adopter could be mainly because the tunnel prolongs the production and generates larger quantities to be sold in the market. This finding is consistent with other research conducted in other parts of Nepal [13], Pakistan [6], and Bangladesh [44], where farmers adopting improved crop varieties produced and sold large quantities of crops in the market. Likewise, tunnel enables farmers to continuously sell tomatoes throughout the year, creating an opportunity to fetch remunerative market prices, especially during short supply. For instance, during the rainy season, the tomatoes' supply declines due to recurring floods in the southern part of the country and neighbouring country India [46]. Farmers adopting tunnel technology are generally located uphill and are not hugely affected by heavy rainfall and flood. Thus, they can supply tomatoes to the market capturing higher prices and earning a higher income. Remarkably, many tunnel farmers have realized these opportunities and thus were found adjusting their crop calendar to harvest and supply maximum quantity during the rainy season to maximize their crop income.

Table 4 also indicates that net crop income is affected by other factors as well. Gender shows a significant negative association with the net crop income, meaning that male farmers earn lower net income than females from tunnel adoption. Male members are involved in off-farm income-generating activities and have less time to manage the farm. Additionally, as noted, the farm size also has a strong positive influence on the net crop income, which can be attributed to economies of scale. The findings are similar to Kenya's research outcome, which showed that the bigger farm size allows farmers to earn higher net crop income [33]. Amongst ethnic groups, there was a significant negative relationship between the Dalit group and net crop income. Dalit farmers earn lower crop income than other communities as they lack financial resources to invest in new technologies such as tunnel houses.

## 4. Conclusions

This study examined the determinants and impacts of tunnel technology adoption amongst smallholder vegetable farmers in Nepal. Our results show that farmers of a relatively younger age with higher education level and larger farm size are more likely to adopt tunnel technology. They are more open to new ideas, take risks and possess better resources. Likewise, people from the so-called lower ethnic group, such as Dalit, are less likely to adopt tunnel technology because they are resource-constrained and lack sufficient financial resources. Notably, the adoption rate is higher if farmers are close to agrovets and tunnel is adopted in the neighbouring farms because it is easier for farmers to access information about the technology and associated benefits and drawbacks.

The treatment model result, which addresses the systematic differences between adopters and non-adopters, suggests that tunnel technology can increase tomato production by 32 tons/ha in a year. The tunnel protects the crop from climate change effects, prolongs production, and makes efficient use of resources. On the contrary, the annual net earnings of tunnel adopters from one hectare of land is just $2440 higher than non-adopters. The treatment model suggests that profit is even lower than $1700, which is not substantial compared to its adoption cost. Adopters must invest annually $12,000 more for tools, materials, labour and other resources, which is incredibly huge compared to the earnings. Thus, there might be colossal cost disadvantages for resource-constrained farmers, making it difficult to adopt the technology. It raises serious concern if tunnel technology is a suitable option for smallholder farmers.

Tunnel house technology, if properly designed and effectively implemented, can positively contribute to three Sustainable Development Goals, such as eliminating poverty (#1), zero hunger (#2), and climate action (#13), as it can increase productivity and profitability and tackle climate change effect. The government should consider reducing the associated installation cost to make it more affordable for smallholder farmers. This could be achieved by introducing effective subsidies, financial or institutional input support. Likewise, the government can impose relevant fiscal policies to control the price of materials and equipment needed in tunnel technology. Additionally, developmental organizations can contribute by providing services and training and supporting farmers in making efficient use of the technology.

*Limitations of the Study*

Despite the interesting findings, our study possesses a few limitations. As our sample size is relatively small, so there is a low degree of generalization of our findings. The result cannot be applied to other diverse contexts. Thus, further quantitative research is needed with a larger sample size to obtain valid, reliable findings that could be extended to smallholder farmers living in other areas. Another shortcoming is related to the complexity of the subject matter. Various observable and unobservable factors affect the farmers' decision to adopt the technology. For instance, market signals such as crops' higher price and market demand might have affected farmers adoption decisions, including their farm income and crop productivity. Likewise, government subsidy, financial policy, infrastructure, and environmental conditions might equally influence farmers decisions. We only observed micro-level factors and included household level socio-economic characteristics to see the effects on adoption decisions. For observable factors, we used socio-economics characteristics such as age, gender, ethnicity, education status, farms size, etc., that are widely used in most of the literature. We used neighbours' farming practices and distance to agrovet as instrumental variables to measure the effect of unobservable factors. Therefore, extensive research focusing on other macro-level observable and unobservable factors is needed to gain more in-depth insights into tunnel technology impacts and adoption.

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## References

1. United Nations. *Report of the Inter-Agency and Expert Group on Sustainable Development Goal Indicators*; UniIted Nations Economic and Social Council: New York, NY, USA, 2016.
2. FAO. *The Future of Food and Agriculture: Trends and Challenges*; Food and Agriculture Organization of the United Nations: Rome, Italy, 2017; ISBN 978-92-5-109551-5.
3. Lowder, S.K.; Skoet, J.; Raney, T. The Number, Size, and Distribution of Farms, Smallholder Farms, and Family Farms Worldwide. *World Dev.* **2016**, *87*, 16–29. [CrossRef]
4. Gentle, P.; Thwaites, R.; Race, D.; Alexander, K.; Maraseni, T. Household and Community Responses to Impacts of Climate Change in the Rural Hills of Nepal. *Clim. Chang.* **2018**, *147*, 267–282. [CrossRef]
5. Markelova, H.; Meinzen-Dick, R.; Hellin, J.; Dohrn, S. Collective Action for Smallholder Market Access. *Food Policy* **2009**, *34*, 1–7. [CrossRef]
6. Ali, A.; Abdulai, A. The Adoption of Genetically Modified Cotton and Poverty Reduction in Pakistan. *J. Agric. Econ.* **2010**, *61*, 175–192. [CrossRef]
7. Tufa, A.H.; Alene, A.D.; Manda, J.; Akinwale, M.G.; Chikoye, D.; Feleke, S.; Wossen, T.; Manyong, V. The Productivity and Income Effects of Adoption of Improved Soybean Varieties and Agronomic Practices in Malawi. *World Dev.* **2019**, *124*, 104631. [CrossRef]
8. Singh, M.; Bhullar, M.S.; Gill, G. Integrated Weed Management in Dry-Seeded Rice Using Stale Seedbeds and Post Sowing Herbicides. *Field Crop. Res.* **2018**, *224*, 182–191. [CrossRef]
9. Gebbers, R.; Adamchuk, V.I. Precision Agriculture and Food Security. *Science* **2010**, *327*, 828–831. [CrossRef]
10. Huang, J.; Wang, Y.; Wang, J. Farmers' Adaptation to Extreme Weather Events through Farm Management and Its Impacts on the Mean and Risk of Rice Yield in China. *Am. J. Agric. Econ.* **2015**, *97*, 602–617. [CrossRef]
11. MOAD Agriculture Development Strategy 2015–2035. 2015. Available online: webhttp://www.doanepal.gov.np/downloadfile/ADS_-FINAL_1542883806.pdf (accessed on 11 August 2020).

12. Bajracharya, D.; Bhuju, D.R.; Pokhrel, J.R. *Science, Research and Technology in Nepal*; UNESCO Kathmandu Series of Monograph and Working Papers: 10; UNESCO: Kathmandu, Nepal, 2006.
13. Budhathoki, N.; Bhatta, G.D. Adoption of Improved Rice Varieties in Nepal: Impact on Household Wellbeing. *Agric. Res.* **2016**, *5*, 420–432. [CrossRef]
14. Atreya, P.N.; Kafle, A.; Suvedi, B.; Shrestha, S. Precision and Protected Horticulture in Nepal. In Proceedings of the 10th National Horticulture Seminar, Nepal Horticulture Society, Kirtipur, Nepal, 1 February 2019.
15. Poudel, R.R. PMAMP Progress Report 2019/20. Available online: https://pmamp.gov.np/sites/default/files/2020-05/PMAMP%20_PMU%20%281%29.pdf (accessed on 7 November 2020).
16. Mukul, S.A.; Byg, A. What Determines Indigenous Chepang Farmers' Swidden Land-Use Decisions in the Central Hill Districts of Nepal? *Sustainability* **2020**, *12*, 5326. [CrossRef]
17. Panthi, J.; Aryal, S.; Dahal, P.; Bhandari, P.; Krakauer, N.Y.; Pandey, V.P. Livelihood Vulnerability Approach to Assessing Climate Change Impacts on Mixed Agro-Livestock Smallholders around the Gandaki River Basin in Nepal. *Reg. Environ. Chang.* **2016**, *16*, 1121–1132. [CrossRef]
18. Kunwar, B.; Maharjan, B. Economic Analysis of Off-Season Tomato Production under Poly-House in Okhldhunga, Nepal. *J. Agric. Environ.* **2019**, *20*, 67–77. [CrossRef]
19. Kumar, P.; Chauhan, R.S.; Grover, R.K. An Economic Analysis of Cucumber (*Cucumis sativus* L.) Cultivation in Eastern Zone of Haryana (India) Under Polyhouse and Open Field Condition. *J. Appl. Nat. Sci.* **2017**, *9*, 402–405. [CrossRef]
20. Kumar, S.; Singh, N.; Chaudhari, D.J. Profitability of Capsicum Cultivation under Protected Condition. *Chem. Sci. Rev. Lett.* **2018**, *7*, 900–904.
21. Khan, A.; Islam, M.; Ahmad, S.; Abbas, G.; Athar, M. Technology Transfer for Cucumber (*Cucumis Sativus* L.) Production under Protected Agriculture in Uplands Balochistan. *Pakistan. Afr. J. Biotechnol.* **2011**, *10*, 15538–15544. [CrossRef]
22. Latif, M.T.; Sher, F.; Hussain, M. Profitability Analysis of Normal Season and Off-season Muskmelon Cultivation in District Sialkot, Pakistan. *Innov. Agric.* **2018**, *1*, 24–27. [CrossRef]
23. FAO Tunnel Farming for Off-Season Vegetable Cultivation in Nepal. Available online: http://www.fao.org/3/CA3560EN/ca3560en.pdf (accessed on 30 May 2020).
24. Kafle, A.; Shrestha, K. Economics of Tomato Cultivation Using Plastic House: A Case of Hemja VDC, Kaski, Nepal. *IJAEB* **2017**, *2*, 10–20.
25. MOALD Krishi Diary 2016. Available online: http://aitc.gov.np/downloadfile/agriculture%20duary-2076-46662.pdf (accessed on 11 July 2020).
26. KC, D.; Maraseni, T.; Jamir, C.; Thapa Magar, R.; Tuladhar, F. Effectiveness of Gravity Goods Ropeways in Market Participation of Smallholder Farmers in Uplands. *Transportation* **2020**, *47*, 1393–1414. [CrossRef]
27. Khonje, M.; Manda, J.; Alene, A.D.; Kassie, M. Analysis of Adoption and Impacts of Improved Maize Varieties in Eastern Zambia. *World Dev.* **2015**, *66*, 695–706. [CrossRef]
28. Kumar, A.; Takeshima, H.; Adhikari, N.; Saroj, S.; Karkee, M.; Joshi, P.K. Adoption and Diffusion of Improved Technologies and Production Practices in Agriculture: Insights from a Donor-Led Intervention in Nepal. *Land Use Policy* **2020**, *95*, 104621. [CrossRef]
29. Pilarova, T.; Bavorova, M.; Kandakov, A. Do Farmer, Household and Farm Characteristics Influence the Adoption of Sustainable Practices? The Evidence from the Republic of Moldova. *Int. J. Agric. Sustain.* **2018**, *16*, 367–384. [CrossRef]
30. Kassie, M.; Shiferaw, B.; Muricho, G. Agricultural Technology, Crop Income, and Poverty Alleviation in Uganda. *World Dev.* **2011**, *39*, 1784–1795. [CrossRef]
31. Stefanides, Z.; Tauer, L.W. The Empirical Impact of Bovine Somatotropin on a Group of New York Dairy Farms. *Am. J. Agric. Econ.* **1999**, *81*, 95–102. [CrossRef]
32. Greene, W.H. *Econometric Analysis*, 5th ed.; Prentice Hall: Upper Saddle River, NJ, USA, 2003; ISBN 978-0-13-066189-0.
33. Kabunga, N.S.; Dubois, T.; Qaim, M. Impact of Tissue Culture Banana Technology on Farm Household Income and Food Security in Kenya. *Food Policy* **2014**, *45*, 25–34. [CrossRef]
34. Krishnan, P.; Patnam, M. Neighbors and Extension Agents in Ethiopia: Who Matters More for Technology Adoption? *Am. J. Agric. Econ.* **2014**, *96*, 308–327. [CrossRef]
35. Michelson, H.C. Influence of Neighbor Experience and Exit on Small Farmer Market Participation. *Am. J. Agric. Econ.* **2017**, *99*, 952–970. [CrossRef]
36. Awotide, B.A.; Karimov, A.A.; Diagne, A. Agricultural Technology Adoption, Commercialization and Smallholder Rice Farmers' Welfare in Rural Nigeria. *Agric. Econ.* **2016**, *4*, 3. [CrossRef]
37. Paudel, G.P.; Gartaula, H.; Rahut, D.B.; Craufurd, P. Gender Differentiated Small-Scale Farm Mechanization in Nepal Hills: An Application of Exogenous Switching Treatment Regression. *Technol. Soc.* **2020**, *61*, 101250. [CrossRef]
38. Shahzad, M.F.; Abdulai, A. Adaptation to Extreme Weather Conditions and Farm Performance in Rural Pakistan. *Agric. Syst.* **2020**, *180*, 102772. [CrossRef]
39. Munshi, K. Social Learning in a Heterogeneous Population: Technology Diffusion in the Indian Green Revolution. *J. Dev. Econ.* **2004**, *73*, 185–213. [CrossRef]
40. Baral, P. Percieved Effectiveness of Information Sources in Meeting Information Needs of Rice Growers in Nepal. *Agric. Socio-Econ. J.* **2020**, *20*, 299–310.

41. Takeshima, H.; Liu, Y. Smallholder Mechanization Induced by Yield-Enhancing Biological Technologies: Evidence from Nepal and Ghana. *Agric. Syst.* **2020**, *184*, 102914. [CrossRef]
42. Abdulai, A.; Huffman, W. The Adoption and Impact of Soil and Water Conservation Technology: An Endogenous Switching Regression Application. *Land Econ.* **2014**, *90*, 26–43. [CrossRef]
43. Kabunga, N.S.; Dubois, T.; Qaim, M. Yield Effects of Tissue Culture Bananas in Kenya: Accounting for Selection Bias and the Role of Complementary Inputs. *J. Agric. Econ.* **2012**, *63*, 444–464. [CrossRef]
44. Schreinemachers, P.; Wu, M.; Uddin, M.N.; Ahmad, S.; Hanson, P. Farmer Training in Off-Season Vegetables: Effects on Income and Pesticide Use in Bangladesh. *Food Policy* **2016**, *61*, 132–140. [CrossRef]
45. Miyata, S.; Minot, N.; Hu, D. Impact of Contract Farming on Income: Linking Small Farmers, Packers, and Supermarkets in China. *World Dev.* **2009**, *37*, 1781–1790. [CrossRef]
46. Ghimire, N.P.; Kandel, M.; Aryal, M.; Bhattarai, D. Assessment of Tomato Consumption and Demand in Nepal. *J. Agric. Environ.* **2018**, *18*, 83–94. [CrossRef]