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電子商務與農民收入和食品支出的相關性分析：菲律賓的實證分析

The Association of E-Commerce with Income and Food Consumption of Farmers: Empirical Evidence from Philippines

曹睿

Patrick Joseph M. Carlos

指導教授：楊豐安

Advisor: Feng-An Yang, Ph.D.

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電子商務與農民收入和食品支出的相關性分析：菲律賓的實證分析

The association of E-Commerce with Income and Food Consumption of Farmers: Empirical Evidence from Philippines

本論文係 PATRICK JOSEPH MENDIOLA CARLOS 君 （學號 R11627040）在國立臺灣大學農業經濟學研究所完成之碩士學位論文，於 2024 年 6 月 24 日承下列考試委員審查通過及口試及格，特此證明。

This is to certify that the Master thesis above is completed by PATRICK JOSEPH MENDIOLA CARLOS（Student ID R11627040） during his studying in the Department of Agricultural Economics at National Taiwan University, and that the oral defense of this thesis is passed on 24th June, 2024 in accordance with decisions of the following committee members:

指導教授 Advisor：楊豐安

口試委員 Committee members：

何[illegible]

楊豐安

林巧涵

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ABSTRACT

From an agricultural industry, the Philippines has shifted to a service-oriented sector throughout the years. This led to the stagnation of the country's food production, which was exacerbated by the transportation and labor issues brought by the recent Covid-19 pandemic. One of the perceived solutions to this challenge is e-commerce. Potentially providing direct market linkage to consumers, this minimizes marketing costs, which increases farmer's income and transportation costs. Coupled with this, a simultaneous rise in food consumption could be expected. The study aims to assess the impact of e-commerce selling on monthly income and food expenditure of Filipino farmers. Additionally, the study investigates several demographic factors that may be involved in deciding whether to engage in e-commerce or not. We use the dataset from the Agricultural Wage Rate Survey as part of the Annual Poverty Indicators Survey, published by the Philippine Statistics Authority. The study uses the Propensity Score Matching Method to acquire a more accurate estimate by matching the untreated group with the treated based on observed famers characteristics. The results show that farmers are inclined to engage in e-commerce if they are younger, women, married, and living in urban areas. Moreover, the study finds that the effect of e-commerce on income was not as pronounced as its effect on food expenditure. After examining the heterogenous effects of their demographic characteristics on income and food consumption, we find that the positive marginal effect of e-commerce is more prominent among farmers who have low educational attainment and rural residences. The research outcome demonstrates the potential of e-commerce as a tool in raising farmers' income and food consumption, thereby paving the way for sustainable economic development through agricultural transformation.

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Chapter 1: INTRODUCTION

The Philippines exhibited promising economic growth in recent years brought by the country's shift towards service-oriented industries. This is caused by rapid industrialization which consequently left the agricultural sector as the poorest in the country (DTI, 2017). The World Bank (2020) reports that the share of the country's agricultural sector declined from 13% to 9.3% between 2008 and 2018. This got worse in recent years as the Philippines' food sector received another set of obstacles brought by the pandemic. At its height in 2020, the Philippines experienced food supply disruption caused by pandemic transport restrictions and agricultural labor mobility issues. The shortage of food supply resulted in rising prices which pervasively reduced the buying power of households, affecting the poor the most (Dy, 2020). Despite this, agriculture remained the highest labor force in the country by employing a quarter of the labor force during the peak of the pandemic. However, it was only able to contribute about 9% of the country's GDP. This underscores the low output per worker compared to other sectors and services (DTI, 2020).

The major sub-industries in Philippine agriculture are crop production, livestock and poultry, fisheries, and forestry. It has evolved throughout the decades, changing from a more traditional way of farming to the integration of innovative technologies. According to Balisacan (2017), land reforms and policy shifts implemented by the transitions in governance affected the sector to a varying degree. The policies previously implemented focused on crop production, technological innovation, and land reform. However, these efforts leave a lot more to be desired. In Figure 1, we observe that the farming industry's contribution to the country's GDP has steadily decreased over the years (World Bank, 2020).

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DTI (2017) has recorded that, while this happens, the service-oriented sector continues to rise.

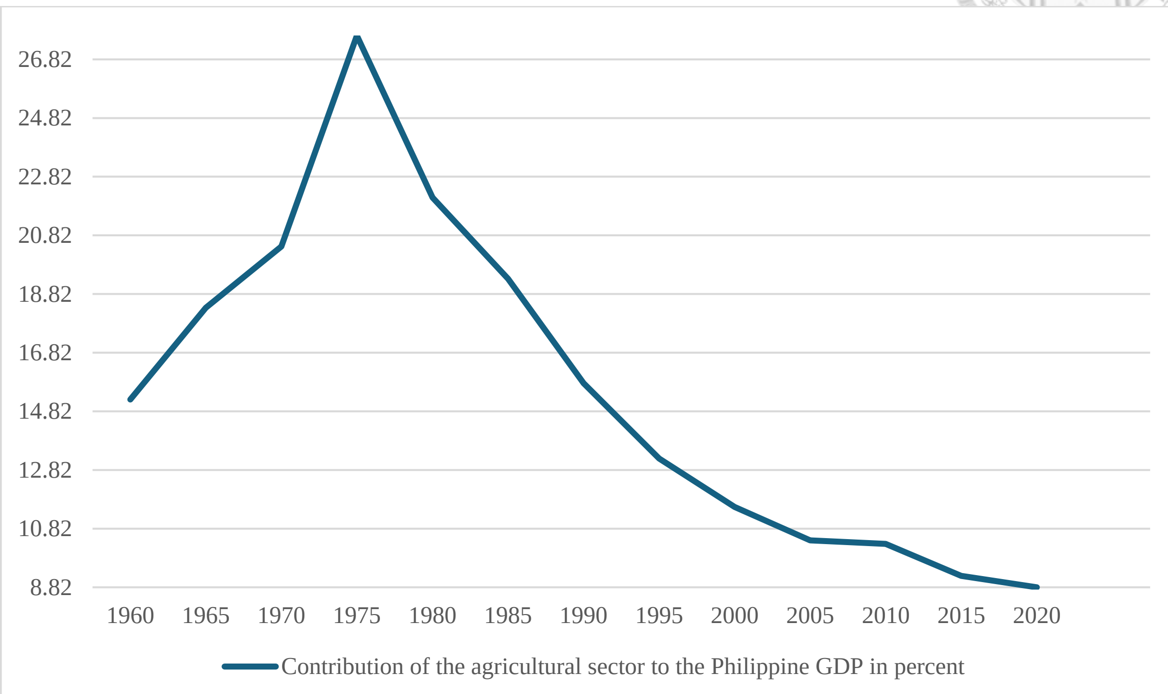

Figure 1. The contribution of the agricultural sector to the Philippine GDP in percent from 1960 to 2022.

Despite this, Philippine agriculture remains a strong foundation of the country's economy even when compared to its neighboring countries. To illustrate, we refer to the study on the comparison of rice production trend in India, Thailand, Vietnam, Malaysia, Philippines, and China from 1990 to 2020 by Yuan *et al.* (2022). We can see in Figure 2 that Vietnam surpassed other countries as it experienced the highest improvement in rice production. After an initial drop, India has slowed but improving yield. Malaysia, Thailand, and the Philippines are consistent throughout the years. With the Philippines having slightly greater yields, it beat Malaysia before 2020. Although China started from the lowest base value, it has also exhibited a great increase throughout the years.

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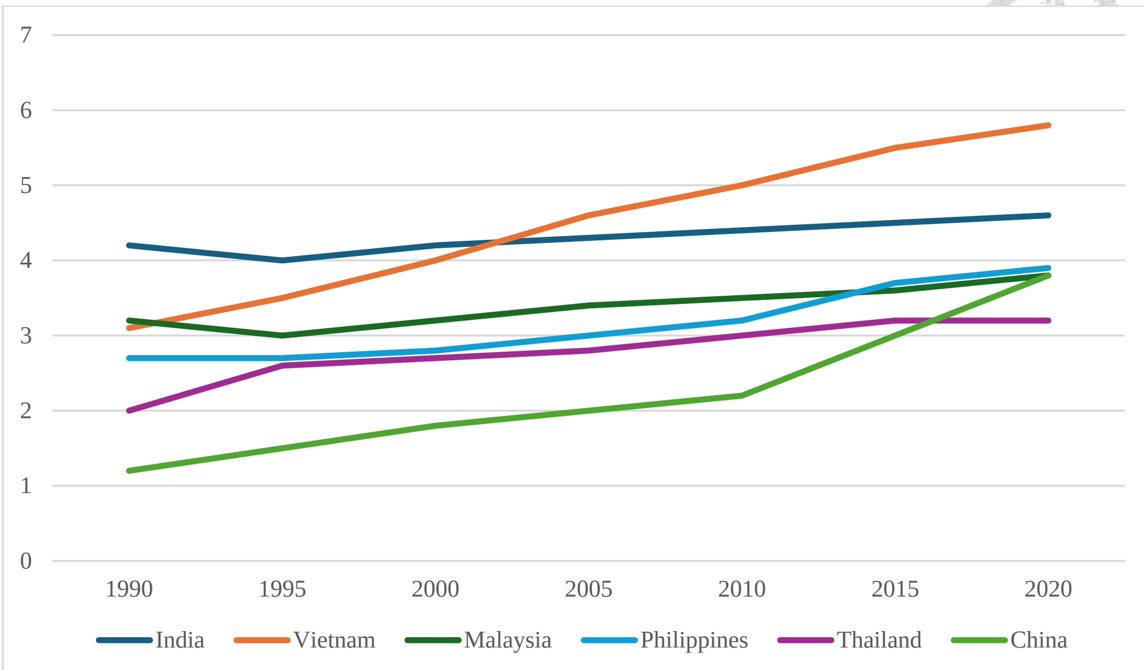

Figure 2. Average yield in rice production (Mg ha^{-1}) of rice in India, Thailand, Vietnam, Malaysia, Philippines, and China from 1990 to 2020.

FAO (2020) reports that the Philippine agriculture does not only play a crucial role in economic development and food security, but it also sustains rural communities and maintains their cultural heritage. It is estimated that the industry supports over 11 million farmers and fishers. Unfortunately, the decline of the agricultural sector affects many. From Quimba & Estudillo's study (2018), the Filipino household income grew from 1991 to 2012 across the Philippines. Yet, we can see that it has become less reliant on agricultural production and wages. Instead, it became more dependent on non-agricultural activities and remittances as seen in Table 1. This implies that activities outside agriculture and migration are more economically beneficial compared to farm production operations.

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Table 1. Household income (USD 2005 PPP) and sources ion income across the Philippines from 1991 to 2012.

Category	Philippines		Near Provinces		Remote Provinces	
	1991	2012	1991	2012	1991	2012
Household income (USD 2005 PPP)	2460	5475	3295	6618	1562	3902
Sources of income (%):						
Agricultural wages	7	5	5	3	12	9
Crop and livestock income	5	2	3	1	11	5
Non-farm wages	65	66	70	71	54	56
Self-employment	4	3	4	3	4	4
Foreign remittances	15	17	15	17	13	17
Domestic remittances	4	7	3	5	5	10

In recent years, the issues worsened after being negatively impacted by the Covid-19 pandemic. During this time, e-commerce became more prevalent due to the ease of access combined with pandemic transportation restrictions. This study aims to delve into this deeper. The two main objectives of this research are to provide insight on how e-commerce selling impacts farmer's income and food consumption; and to identify the factors that affect the farmer's decision to engage in e-commerce selling. The research uses a dataset captured at the height of the pandemic to deepen our understanding on how the farmer's condition during the critical time period.

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Chapter 2: LITERATURE REVIEW

2.1. The Philippine agriculture during Covid-19

As documented by Rappler (2021), Covid-19 pandemic in the Philippines started on January 30th, 2020, when the first confirmed case. She was a 38-year-old female Chinese national from Wuhan arrived. On March 12th, 2020, former President Duterte placed Metro Manila under community quarantine. Four days later, this was extended to Luzon and added more rules to improve the fight against virus transmission. This was then implemented across the other regions. A year later, March 29, 2020, the government reverted its relaxed guidelines as cases attributed to new variants surged. In April 2021, the vaccination program started to pick up pace. A month later, the government once again relaxed its community quarantine protocols. After a few months of vaccination roll out, the government continued to further loosen its quarantine restrictions.

The Covid-19 pandemic exposed other problems related to agricultural land utilization, aging farmer demographics, and inadequate infrastructure. Along with environmental risks brought by climate change and natural calamities, the Philippine government's effective response and recovery efforts is more obstructed (Briones, 2021). The World Bank (2020) reports that addressing these challenges requires interventions that specifically target the enhancement of productivity and sustainability of small-scale farms. Investment in research and development, improved agricultural practices, and better market access are viewed as key solutions. One of the perceived potential tools in realizing this is to mobilize agricultural marketing through the participation of small-holder farmers in e-commerce (Ang, 2020). The pandemic opened a unique opportunity to promote the reconstruction of an agri-system that is more resilient, inclusive, competitive, and

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sustainable. Additionally, the transformation of the country's food and agri-systems is critical in overcoming the pandemic to secure a sufficient, affordable, and healthy food supply. Market linkage is integral in restoring normal market functions during crisis-related disruptions. It can realize inclusive local economic development for the stakeholders involved while increasing business transaction efficiency in the city (World Bank, 2020). This is why e-commerce and supply chain digitalization are positioned as significant contributors in agricultural innovation by connecting smallholder farmers directly to businesses and consumers. This served as a significant basis for conceptualizing this research as various entities, including public and private offices, are investing in agricultural e-commerce.

2.2. Government programs and policy support in 2020

The agricultural sector was severely affected by the economic shocks at the height of the Covid-19 pandemic. The Philippine government tried to relieve this through the Social Amelioration Program (SAP). It involved provision of financial assistance, ranging from Php. 5,000.00 to Php. 8,000.00 per month. The pandemic program was an inter-government agency initiative to aid eligible beneficiaries, including low-income families, and informal workers. It aimed to alleviate the negative impact of the pandemic to households, focusing on social and economic effects (DSWD, 2020).

While SAP made a significant effort, it faced challenges in its implementation. Its targeting accuracy was criticized as there were families claiming to be eligible but failed to receive benefits. On the other hand, there were ineligible families who were reported to have received financial assistance (Cabuenas, 2021). The assistance was delivered through house-to-house distribution and claiming at local government offices. The manual handling of

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assistance made it more difficult to reach the targeted beneficiaries, especially the most vulnerable and affected who lived in far-flung and mostly isolated areas. In relation to this, there were delays due to administrative processes and logistical issues. The effectiveness of the program varied based on individual experiences. Some beneficiaries responded with having positive outcomes with the cash assistance helping them meet their basic needs during the crisis. The challenges faced in program implementation negatively affected its overall efficiency (Muzones, 2022).

Alongside SAP, the Philippine government implemented "Plant, Plant, Plant Program" through the Department of Agriculture. It aimed to benefit farmers, fishers, and consumers nationwide by increasing the country's food adequacy during the pandemic. This included the "Rice Resiliency Project," to increase rice sufficiency from 87% to 93%. Other programs focused on capital assistance to empower local farmers or those interested in venturing into agricultural entrepreneurship. This included "Intensified Use of Quality Seeds and Modern Technologies," "Additional *Palay* Procurement Fund," "Expanded SURE Aid," "Social Amelioration for Farmers and Farm Workers," and "e-*KADIWA ni Ani at Kita* Direct Marketing Program."

2.3. Post-pandemic and agricultural e-commerce

Amidst the pandemic, the Philippine agriculture remained resilient as it adapted to the new norms. The integration of digital solutions allowed the continuation of agricultural produce marketing. The Department of Agriculture initiated several programs to support the farmers. The key focus of the programs are productivity, market access, and resilience to future disruptions which were mentioned earlier. The Plant, Plant, Plant program was the government's main plan in solving the issues faced.

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The perceived gap of the government's efforts to revitalize the agricultural sector is its focus on productivity instead of entrepreneurial activities (Santiago, 2015). Department of Trade and Industry undersecretary, Ramon Lopez (2015), stated in his speech that farmers should be equipped with an entrepreneurial mindset to maximize the support they receive. He added that smallholder farmers should be familiarized with business models that would improve their agricultural production and be given access to market their produce to bigger companies. He also mentioned that it would lead to improved agricultural production and greater income generation, allowing efficient and inclusive agricultural modernization and development. This corresponds with *Ambisyon Natin* 2040, a long-term development plan for the Philippines where agriculture is included in its priority sector to invest in. This is why e-commerce is seen as a potential solution in revitalizing the post-pandemic Philippine agriculture.

The adoption of e-commerce in agriculture during and beyond the pandemic encouraged the farmers and agricultural businesses to use digital platforms in marketing their products. It helped them eliminate middlemen, allowing them to have direct communication with businesses and end-consumers. Aside from restoring their linkages with former clients, it helped them network with new ones. This shift has been supported by both private and public initiatives through developing digital infrastructure and provision of training for farmers. The Asian Development Bank (2021) reported that digitalization and e-commerce are key to rebuilding resilient food systems in the Philippines. They emphasized that this is particularly important in maintaining the flow of goods during disruptions, not only by Covid-19, but also by natural calamities or other crises. In support of this, a study by Dela Cruz *et al.* (2022) highlighted that e-commerce adoption among farmers increased income

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and market access. This helped them achieve higher sales and better pricing for their products as compared to those who do not participate in e-commerce. The study demonstrated that providing farmers with a platform to market their products through e-commerce facilitated a more inclusive economic development.

While e-commerce seems to be a very promising tool, the country still faces obstacles in fully integrating it into the agricultural sector. Muñoz *et. al* (2020) reports that many of the primary sectors are left behind in terms of technological innovation because of poverty and illiteracy. They concluded that, aside from the provision of government-sponsored communications technology, education and financial literacy should be implemented to enhance their entrepreneurial capabilities and socioeconomic status. Furthermore, the consumers, the public administration, and the primary sectors would appreciate the development of a market mobile application and the convenience it could provide. Another article that discussed local agricultural e-commerce is Jain and Carandang's (2018) Development of an online Laguna agricultural trading center. The research's output was the Online Laguna Agricultural Trading Center, an e-commerce website. It aimed to enhance the marketability of farm products in Laguna, Philippines by directly connecting farmers with consumers. The research concluded that the e-commerce website was acceptable and useable for both farmers and consumers. It also mentioned that the developed system improved the marketability of farm products in Laguna, while allowing for faster sales, wider reach, and greater income. These findings align with the suggestion to invest in the digitalization of agricultural marketing. By taking advantage of digital marketing platforms, farmers can improve their incomes.

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Outside the Philippines, the study by Yi, *et. al*. (2023) provides strong evidence that e-commerce is related to income growth in Chinese farmers from various provinces. Additionally, the study observed significant income boost at the start, which eventually decreased at a certain point. They have also identified the benefits of digital finance. Specifically, it enhances agricultural entrepreneurial activities by easing access to credit and encouragement of innovative activities. In another study, Hong, *et. al.* (2020), published in Food Policy journal that e-commerce adoption significantly increases farmer's income. Using data on agricultural areas in rural China, they found that e-commerce platforms enable farmers to access broader markets, allow for appropriate pricing, and reduce marketing costs. All of these contribute to higher income generation. Still in rural China, a study by Ferrante (2015) from the Journal of Rural Studies supports the previous claim. The study was specifically done on Taobao villages in China where she found active participation in e-commerce of the villagers which notably increases household income and general economic well-being as compared to non-participants.

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Chapter 3: DATA AND DESCRIPTIVE STATISTICS

3.1. Data source

The study sources its data from the Annual Poverty Indicators Survey (APIS). It is a national survey that contains information on Filipino household conditions published by the Philippine Statistics Authority (PSA). It collects data on poverty indicators. This information is relevant in the Philippine government's formulation of poverty alleviation programs and policies. APIS features a wide range of topics such as income, expenditure, education, health, housing, and access to basic services. This information provides a general view of household welfare. The survey is conducted annually to allow access to up-to-date information. It also uses appropriate sample sizes to ensure data reliability. The data collection involves personal interviews with household members with structured questionnaires.

Under APIS is the Agricultural Wage Rate Survey (AWRS). Like APIS, its aim is to provide information on Filipino household welfare, concentrating on agricultural households. Its main goals are to determine national and regional variations in wage rates by type of labor, gather gender-based labor data on wage rates, and assess women's participation in agricultural activities. This survey estimates the average wage rates of agricultural farm workers across four major crops in the country. This includes palay, corn, coconut, and sugar cane farmers production. It used a sample survey data approach which identified households that hired farm workers within the specified period and were knowledgeable about the farm activities.

The methodologies of AWRS follow the standards of another agricultural survey, Palay and Corn Production Survey (PCPS). It has nationwide geographic coverage, focusing on the main producers of the crops mentioned. However, as with the PCPS, Batanes is not

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included in the survey. Additionally, Sulu was also excluded since there were incidences where rice farmers did not employ any laborers for their farming activities. The survey tools used included questionnaires, manuals, and field supervision in collecting and processing data. It must be noted that, while the Philippine Statistics Authority reported the survey as "Agricultural Wage Rate 2017," the data used in this study was from January to June 2020.

The control variables the study uses covers both demographic and socio-economic characteristics of farmers. These include the respondent's sex (*male*), age (*age*), marital status (*marital_status*), residence (*urban*), educational attainment (*educ_a, educ_b, educ_c, educ_d*), computer ownership (*pc*), and availability of internet access at home (*internet*). We assigned all control variables as binary variables except for age. To do this, we assigned male, living in urban area, ownership of a computer, and internet access as default values wherein 1 indicates the information is true to the individual, 0 if otherwise. The marital status variable in AWRS includes several options including married, single, widowed, divorced, annulled, and unknown. However, the responses aside from the first two options comprise only a small fraction of the data. Therefore, the farmers who identified as single, widowed, divorced, annulled, and unknown were all categorized as "single" in this study. They are represented by 0 in the control variable *married*.

AWRS follows the Philippine educational system for the highest level of education attained variable. The study simplifies this by grouping the responses into binary variables *educ_a, educ_b, educ_c,* and *educ_d* which represent the required years of education to attain them. Variable *educ_a* indicates having at most 6 years of education which includes no grade completed, pre-school, grade 1 to grade 6, and elementary undergraduate; *educ_b* indicates

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having at 7 to 10 years of education which include junior high school undergraduate and junior high school graduate; *educ_c* indicates having 11 to 16 years of education which includes undergraduate and graduate of any senior high school programs; and *educ_d* indicates having 17 or more years of education which includes post-graduate programs. After excluding observations with missing values, we end up with 16,457 observations.

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3.2. Theoretical Intuition of Variables

Table 2. Key variables and their justification.

Variable	Justification
	Output Variables
Average monthly income (*ami_6)*	Income is a universally recognized indicator of household welfare. Its comprehensive measurements allow researchers to gauge economic status. Specifically, it shows the person's capacity to meet essential needs and services. This implies that higher income provides opportunities to better living standards, greater purchasing power, and wider access to goods (OECD, 2013).
Average food consumption *(afc_6)*	Supporting the previous treatment variable, food expenditure is an important economic indicator for Filipino agricultural households. This allows us to observe their consumption patterns and economic status. According to Valera et al. (2022), data on food consumption shows the household's capability to respond to income changes and market shocks. This allows researchers to reflect not only on the household's economic well-being, but also help in assessing economic stability and food security (Coates, *et al*., 2021).
Treatment Variable	
Participation in e-commerce selling *(e_sell)*	E-commerce allows wider access to markets. With the possibility of direct communication between buyer and seller, transaction and marketing costs are reduced. The technology of e-commerce platforms paves the way for ease of price discovery, market efficiency, and accessibility to selling. Considering all of these, household income is expected to improve (UNCTAD, 2019). Furthermore, the World Bank (2020) reports that digital platforms can empower small-scale producers through direct market linkages. For instance, producer to consumer transactions bypass traditional market intermediaries which may lead to higher profits.

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3.3 Outcome variables

To see the effects of e-commerce selling on monthly income, we treat this as an outcome variable. Specifically, we get the average monthly income per quarter from January to June 2020 in Php (*ami_6*). For the other outcome variable, we consider family's average monthly food consumption per quarter from January to June 2020 in Php (*afc_6*). We get these values by computing the mean average of the individual's monthly food consumption from the first two quarters of 2020.

In Figure 3, we see the distribution of the average monthly income (*ami_6*) showing a substantial skewness. This indicates that many farmers have low monthly income while only very few have high monthly income. This demonstrates a wide disparity in income levels among farmers.

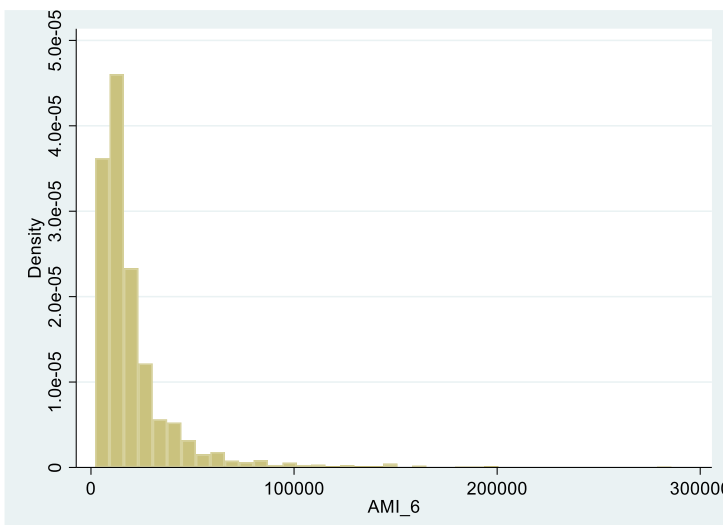

Figure 3. Distribution of average monthly income (*ami_6*).

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In parallel, the same could be observed in the distribution of the average monthly food consumption (*afc_6)* in Figure 4. The positive skew shows that most families have low monthly food consumption while very little have high consumption. It implicates a weighty variability in food consumption patterns among different households.

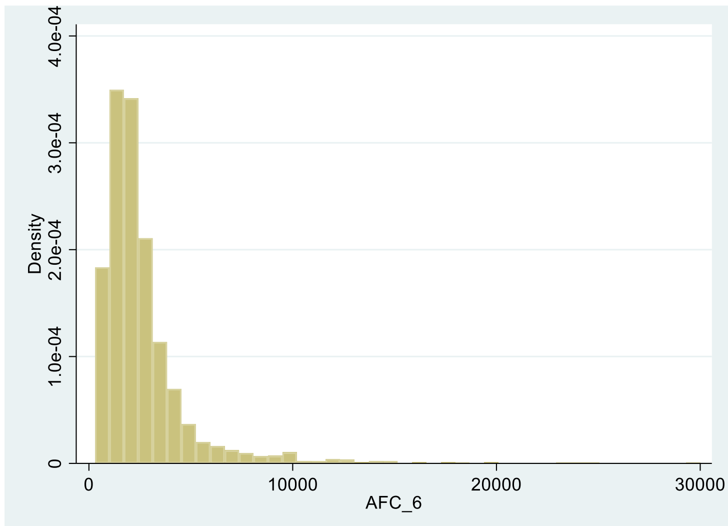

Figure 4. Distribution of average food consumption (*afc_6*).

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3.4. Treatment variable

In this study, the treatment variable focuses on whether the farmers participate in e-commerce selling (*e_sell*). However, the data source did not specify what goods were sold. Therefore, it must be noted that the study does not pertain to selling of agricultural produce online. Instead, we define the treatment variable *e_sell* as the engagement of the farmer in e-commerce selling itself, regardless of the goods sold. Participation in e-commerce selling is a binary variable. 1 is the code if the individual has participated in e-commerce selling for the past 6 months, 0 if otherwise.

3.5. Descriptive statistics

The study considers data from AWRS with 16,457 observations collected in the Philippines during the first half of 2020. Table 3 shows the description of each variable while table 4 shows the pre-matching values. According to the statistics, 73.74% of the farmers are men and their average age is 49 years old. This ranges from 13 to 98 years old. About 61.70% reside in urban areas and 73.80% are married. Only 39.09% of the farmers attained 11 to 16 years of education and 1.29% have more than 17. As for the rest, 19.66% have at most 6 years of education and 36.96 have 7 to 10. 39.09% of the farmers own computers in their households with 28.46% having internet access.

For the outcome variables, the average monthly income is Php. 21,276.14 while average monthly consumption is Php. 2,645.49. However, we observe a wide gap in these variables. Monthly income starts from Php. 2,000.00 up to Php. 300,000.00. In parallel, average food consumption starts from Php. 300.00 up to Php. 30,000.00. This imply that the sample included larger agricultural business owners as outliers. However, the average values

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are closer to minimum value than the maximum. This indicates many of the participants surveyed are smallholder farmers. For the treatment variable, only 12.69% of the farmers engage in e-commerce selling which suggests that this technology is still relatively new to the sector.

Table 4 presents the mean values of control variables separately for respondents who participated in e-commerce and those who did not. It can be observed that around three-quarters of the farmers are married and males, nearing their fifties whether they participate in e-commerce selling or not. We see stark differences regarding the other variables. For instance, there are more urban farmers who participate in e-commerce selling (73.9%) than those who do not (59.9%). Additionally, years of education have varied values. There were more farmers with 6 or less, and 16 or less years of education who participated in e-commerce selling. However, there were more farmers with 10 or less years of education who did not participate in e-commerce selling. Furthermore, having a personal computer and internet at home indicates higher means in participating in e-commerce (58.1% and 43.3%) than those who do not (36.9% and 26.3%.) The wide differences in the covariates in both treatments further motivates the use of PSM to construct a control group that is like the treat group.

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Table 3. Descriptive statistics of the variable, pre-matching.

Variable	Description	Mean	Std. dev.	Min	Max
ami_6	Average monthly income	21276.140	24632.740	2000.00	300000.00
ln_income	Logarithmic value of average monthly income	9.627	0.760	7.601	12.612
afc_6	Average monthly food consumption	2645.488	2432.851	300.00	30000.00
ln_consumption	Logarithmic value of average monthly food consumption	7.645	0.642	5.704	10.309
e_sell	Participation in e-commerce selling	0.127	0.333	0	1
male	= 1 if male, otherwise	0.737	0.440	0	1
age	Age	48.915	14.045	13	98
marital_status	= 1 if married, otherwise	0.738	0.440	0	1
urban	= 1 if living in urban area, otherwise	0.617	0.486	0	1
educ_a	= 1 if has at most 6 years of education	0.197	0.397	0	1
educ_b	= 1 if has at most 10 years of education	0.400	0.490	0	1
educ_c	= 1 if has at most 16 years of education	0.391	0.488	0	1
educ_d	= 1 if has at least 17 years of education	0.0128	0.113	0	1
pc	= 1 if household owns a personal computer, otherwise	0.396	0.489	0	1
internet	= 1 if household avails internet connection, otherwise	0.284	0.451	0	1

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Table 4. Descriptive statistic of individual characteristics individual t-test, pre-matching.

Variable	Mean Treated	Mean Control	%bias	t-test (t)
male	0.703	0.742	-8.8	-3.80***
age	47.835	49.072	-8.9	-3.76***
marital_status	0.773	0.733	9.2	3.85***
urb	0.739	0.599	29.9	12.29***
educ_a	0.113	0.209	-26.3	-10.33***
educ_b	0.391	0.401	-2.1	-0.90
educ_c	0.487	0.377	22.4	9.69***
educ_d	0.009	0.013	-4.1	-1.64*
pc	0.581	0.369	43.3	18.64***
internet	0.433	0.263	36.2	16.18***

*,**, *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

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Chapter 4: METHODOLOGY

Aiming to assess the effects of participation in e-commerce selling to farmer's income and food consumption among agricultural households in the Philippines, the Ordinary Least Squares (OLS) is a straightforward statistical tool that could be used. However, it could provide biased estimates because agricultural households decided whether to participate in e-commerce selling or not by themselves. This decision may introduce selection bias and endogeneity as it may involve other unobserved factors that may also affect household income and consumption (Woolridge, 2010). Additionally, this study considers that the farmer's decision whether to participate in e-commerce selling is for them to settle based on several factors. We also consider that the data the study uses is observational in nature. This means that OLS may not be able to control cofounding variables that influence both the treatment and outcome variables. With all of these considered, it is necessary to use a non-experimental method to address these obstacles and carry our study (Austin, 2011).

To carry out our objective, we need to know the difference between the treatment and the control. Since we cannot observe both in one individual simultaneously, matching them is the alternative. In matching, individuals from the treatment and the control group with similar characteristics are paired together. The value of their differences and their significance are then identified. This provides a more accurate estimation of the effect of the treatment policies (Caliendo & Kopeinig, 2008). This can be done through Propensity Score Matching (PSM). PSM is a statistical technique used in estimating the effect of a treatment on an outcome. It is a well-known tool that is appropriately used in estimating causal treatment effects. Because of this, many researchers use PSM for different purposes. In relation to the study, PSM has also been widely used for evaluation of market policies

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(Caliendo & Kopeinig, 2008). It has been specifically applied to several agricultural research such as the assessment of the impact of agricultural interventions on household outcomes (Wordofa *et al*., 2021), the effect of agricultural technology transfer to productivity of smallholder farmers (Samanta, 2023), and the influence of agricultural credit facilities on farm production (Osabohein, *et al*. 2020), to name a few.

It is most useful when random assignment is not feasible in observational studies like our dataset from AWRS (Rubin, 2001). In this process, the propensity scores of farmers who participate in e-commerce selling are matched with non-participants who share the same characteristics as them. To do this, we first estimate the propensity scores using probit regression. This enables the estimation of the probability of participating in e-commerce selling based on observed variables. This is specified by the equation:

$$p(X)=P(T=1|X)=\Phi(\beta_0+\beta_1X_1+\beta_2X_2+\ldots+\beta_kX_k)$$

where $p(X)$ is the propensity score of the probability of a farmer to participate in e-commerce selling, and Φ denotes the cumulative distribution function (CDF) of the standard normal distribution given the observed covariates; β_0 is the intercept term; T is the treatment variable (*e_sell*) and X_k are the covariates (*male, age, marital status, urban, educ_a, educ_b, educ_c, educ_d, pc, and internet*).

After estimating the propensity score *p(X),* we calculate the average effect of the treatment (ATT). ATT is a necessary step of the process as it specifically targets individuals who are engaged in e-commerce selling. This allows us to clearly identify its impact on

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farmer's income and food consumption through the comparison of the actual income of the farmers who engage in e-commerce selling with their counterfactual income had they opted not to participate (Rubin, 2001). It is specified by the equation:

$$\mathrm{ATT} = \frac{1}{\mathrm{N_t}} \sum_{\mathrm{i} \in \mathrm{Treated}} (\mathrm{Y_{1i}} - \mathrm{Y_{0i}})$$

where $\mathrm{N_t}$ is the number of treated units; $\mathrm{Y_{1i}}$ observed outcome variable for the treated units; $\mathrm{Y_{0i}}$ is the counterfactual income for treated units, estimated using the matched control units.

Another consideration in doing PSM is the matching algorithm to be used. According to Smith (2008), any of the models could be used. Below I provide an overview of the common matching estimators.

Nearest Neighbor (NN) Matching matches each treated unit with the nearest control unit on the propensity score, hence its name. NN includes common support condition which implies that there is enough overlap between the propensity scores of the treated and untreated units. This reduces bias while improving match quality, which ultimately improves the validity of the estimates. However, it can be sensitive to the differences in propensity score distribution. This leads to poor quality matches and increased bias (Caliendo & Kopeinig, 2008).

Kernel matching (KM) constructs a counterfactual outcome by using a weighted average of all control units. This generally leads to a lower variance because of the additional information included and improves the quality of estimates. Using this matching method calls for the proper imposition of the common support condition to avoid using poor matches (Smith, 2008).

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Finally, we also consider local linear regression (LLR) matching. It is more adaptable than the previously mentioned matching methods. It includes a linear term in the propensity score which is useful if there are gaps.

Because there is no analytic standard errors for matching estimators, this study uses the bootstrapping method to calculate the standard errors.

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Chapter 5: RESULTS

5.1. Propensity score estimation

Table 5 represents the propensity score estimation model. The values include coefficients and standard errors. The purpose of this model is to estimate the likelihood of a farmer to participate in e-commerce selling based on various demographics and social characteristics in the first column. We observe that being married, residing in urban areas, having higher education, owning a personal computer, and having access to the internet all increase the likelihood of a farmer to participate in e-commerce selling. On the other hand, being male and older decrease it.

Table 5. Propensity score estimation.

Variable	Coefficients	Std. err.
male	-0.222***	0.035
age	-0.004***	0.001
marital_status	0.229***	0.037
urban	0.252***	0.028
educ_a	0.316**	0.130
educ_b	0.473***	0.127
educ_c	0.458***	0.126
educ_d	0	(omitted)
pc	0.355***	0.030
internet	0.180***	0.032

*,**, *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

5.2. Post-matching results

With the use of PSM, we match the propensity scores of the farmers who participated in e-commerce selling to those who did not while reflecting on their demographic characteristics: gender, age, marital status, type of residence, years of education, ownership

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of a personal computer, and internet access. After getting the post-matched data in Table 6, we recognize the imbalances in the pre-matched data in table 4 as shown by the reduction in percent bias. This shows better balancing between the treated and control groups because of their close similarities. For example, the bias dropped from 8.8% to 4.7% for gender, from 8.9% to 5.8% for age, and 9.2% to 3.3% for marital status. There are also considerable reductions from 29.9% to 4.8% for residence, from 26.3% to 5.6 for having 6 years of education or less, from 43.3% to 0.8% for owning a personal computer, and from 36.2% to 0.5% for having internet access. We see that all the variables except *age*, *educ_a*, and *educ_d,* are not statistically different in both treatments, implying a relatively successful covariate balancing.

Table 6. Descriptive statistic of individual characteristics, individual t-test, covariate balance, post-matching.

Variable	**Mean Treated**	**Mean Control**	**%bias**	**%reduct bias**	**t-test**
male	0.703	0.724	-4.7	46.2	-1.51
age	47.835	47.027	5.8	34.7	1.94*
marital_status	0.773	0.787	-3.3	63.8	-1.12
urban	0.739	0.716	4.8	83.9	1.63
educ_a	0.113	0.092	5.6	78.5	2.19**
educ_b	0.391	0.405	-2.8	-35.1	-0.92
educ_c	0.487	0.499	-2.4	89.2	-0.77
educ_d	0.009	0.004	5.0	-21.4	2.12**
pc	0.581	0.577	0.8	98.2	0.25
internet	0.433	0.430	0.5	98.6	0.16

*,**, *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

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To further assess the quality of matching, the study compares the pseudo-R^2 before and after matching. According to Sianesi (2004), this value indicates the proportion of variance in the treatment variable that can be explained by covariates pre-matching. Great matching quality is suggested by a lower pseudo-R^2 sample after matching. Table 7 shows this, with the pseudo-R^2 value from matched samples (0.003) being lower than the unmatched (0.048). Similarly, a smaller post-matching value suggests reduced differences between the groups. In the results, the post-matching χ^2 (16.42) is smaller than the pre-matched (601.08). Finally, an insignificant p-value ($p > \chi^2$) after matching indicates that there are no statistically significant differences in covariates between the treatment the control groups. In our data, however, the $p > \chi^2$ is conventionally significant at 10% but not at 5% and 1%. Although there are some remaining imbalances, they are much less pronounced than the pre-matched data.

Table 7. Absolute bias, pseudo-R^2 and χ^2.

	Pseudo-R^2	χ^2	$p > \chi^2$
Unmatched	0.048	601.08	0.000
Matched	0.003	16.42	0.059*

*,**, *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

5.3 Estimation of ATT.

We first show the distributions of propensity score between the treatment group and control group. Its main function is to check for the overlap between the propensity scores of the treatment and the control groups. Having sufficient overlap allows each treated unit to find adequate control units with similar propensity scores. Overall, we observe that there is sufficient overlap between the two propensity score distributions.

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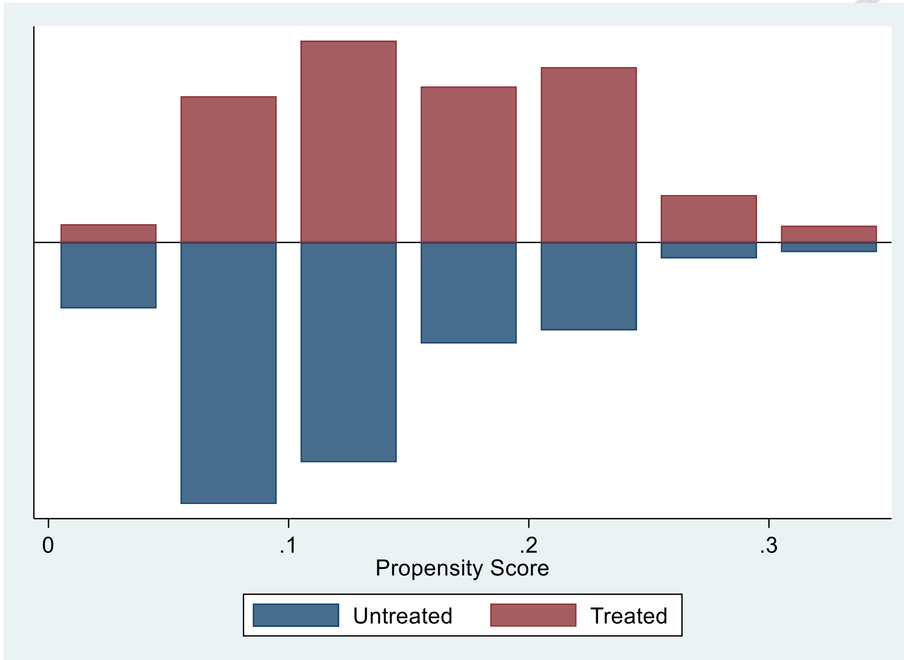

Figure 5. Propensity score graph.

Table 8 shows the matching results of ATT. The study considers four different algorithms to control the pre-existing difference between treated and control groups. This provides a more reliable estimate of treatment effects. The unmatched samples of average monthly income show significant positive difference compared to the control groups. This indicates higher income for those who engage in e-commerce selling. However, the differences are greatly reduced across all matching algorithms with inconsistent values. For average monthly income, NN and KM yield 10% significance level while LLR yields 1%. On the other hand, average monthly food consumption yields 10% significance level for NN and as high as 1% for NN, KN, and LLR.

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Table 8. Matching results of ATT using 4 matching algorithms.

Matching Algorithm	Difference	Std. Err	Bootstrap (200) std. err
		Average Monthly Income	
Unmatched	5177.422***	575.398	
NN	763.510	1462.960	1538.760*
KM	1081.930*	627.356	571.554*
KM (0.1 bw)	768.957	631.798	590.676
LLR	847.692	1462.960	614.084***
		Average Monthly Food Consumption	
Unmatched	687.180***	56.716	
NN	- 29.573	182.925	172.209*
KM	282.610***	65.781	61.561***
KM (0.01 bw)	375.499***	65.469	63.206***
LLR	270.440	182.925	65.413***

*,**, *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

We further examine the matching results of ATT using logarithmic values of the outcome variables we generated earlier (*ln_income* and *ln_consumption*) in table 9. After regressing the normalized values for income and food consumption, we see that the unmatched samples for both yield significant differences. This proves higher income and food consumption for e-commerce participants. Applying the four matching algorithms shows different results. For monthly income, NN yields a 10% significance level, while KM and LLR algorithms yield as high as 1%. For the average monthly food consumption, the NN algorithm yields a 5% significance level, while KM and LLR algorithms yield as high as 1%.

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Table 9. Matching results of ATT using 4 matching algorithms and the logarithmic values of the outcome variables.

Matching Algorithm	Difference	Std. Err	Bootstrap (200) std. err
	Average Monthly Income		
Unmatched	0.247***	0.018	
NN	0.621	0.493	0.033*
KM	0.066***	0.889	0.017***
KM (0.1 bw)	0.106***	0.018	0.019***
LLR	0.063*	0.049	0.015***
	Average Monthly Food Consumption		
Unmatched	0.231***	0.015	
NN	0.072*	0.044	0.034**
KM	0.096***	0.015	0.012***
KM (0.01 bw)	0.072*	0.044	0.016***
LLR	0.093**	0.044	0.013***

*,**, *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

In tables 10 and 11, we observe the heterogenous effects of the demographic characteristics on the outcome variables. This allows us to understand how they influence the impact of e-commerce on the farmer’s income and food consumption. The results display a variety of differences and inconsistent significance levels across the variables. It is notable that in analyzing the matching algorithms for average monthly income, the propensity scores for living in rural areas and having at most 6 years of education show consistent significant levels. This is the same for average monthly food consumption where the demographic characteristics that displayed significant differences were also those living in rural areas and having at most 6 years of education.

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Table 10. Heterogenous effects of demographic characteristics on farmer's income.

Demographics	Value	Unmatched	NN	KM	KM(0.1 bw)	LLR
Gender						
Male	Difference	5941.415***	-622.226	1396.259*	2461.385***	821.236
	Std. Error	675.954	2033.074	748.016	742.779	2033.074
	Bootstrap		1859.502	804.521*	782.508**	930.3827
Female	Difference	3144.214***	4903.465***	79.508	886.204	223.370
	Std. Error	1098.788	1805.684	1156.186	1151.769	1805.684
	Bootstrap		1638.385**	1013.658	1121.299	894.066
Civil Status						
Married	Difference	5546.520***	-553.981	1380.337*	2043.876***	826.878
	Std. Error	650.604	1826.854	782.863	699.712	1826.854
	Bootstrap		1681.59	673.059	693.288**	670.365
Not married	Difference	3819.498***	4559.926*	108.876	2129.607	1166.671
	Std. Error	1226.351	2390.018	918.363	1384.746	2390.018
	Bootstrap		1714.495**	673.059	1352.006	1320.795
Residence						
Urban	Difference	4572.604***	-152.500	1380.337*	2145.673***	1175.376
	Std. Error	697.301	1989.916	782.863	780.162	1989.916
	Bootstrap		1921.466*	1297.161**	896.972**	682.177*
Rural	Difference	4236.628***	2649.536	108.876	1808.762***	-1305.074
	Std. Error	1037.186	1936.644	918.363	909.568	1936.644
	Bootstrap		2050.446	976.615	1009.821*	985.033
Years of Education						
Has at most 6 years of education	Difference	5927.359***	4809.786***	4938.401***	5657.325***	3942.128***
	Std. Error	897.707	2118.030	1408.281	1406.700	2118.030
	Bootstrap		1562.488**	1242.813***	1393.064***	1276.400**
Has at most 10 years of education	Difference	997.231***	-1949.527	-1346.870***	-542.267	-1697.565
	Std. Error	505.721	1451.973	419.550	414.997	1451.973
	Bootstrap		1012.509	446.741**	338.574	435.421***

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Has at most 16 years of education	Difference	5579.828***	-1741.337	2023.118*	2622.048***	2720.282
	Std. Error	1088.927	3138.919	1139.990	1135.921	3138.919
	Bootstrap		2885.8*	965.28	1025.995**	1248.498**
Has 17 or more years of education	Difference	-6135.233	13794.235	-1591.478	-2162.895	-4504.465
	Std. Error	11801.756	17109.238	7545.775	7319.486	17109.238
	Bootstrap		11199.48	7590.685	7411.439	8184.708

*,**, *** indicate statistical significance at 10%, 5%, and 1% levels, respectively. The bootstrap standard errors are reported.

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Table 11. Heterogenous effects of demographic characteristics on farmer's food consumption.

Demographics	Value	Unmatched	NN	KM	KM(0.1 bw)	LLR
Gender						
Male	Difference	822.918***	-263.932	359.507***	473.062***	288.734
	Std. Error	68.118	260.927	81.060	80.585	260.927
	Bootstraps		196.934	81.060***	75.084***	209.784
Female	Difference	366.265***	635.940***	75.709	144.207	115.729
	Std. Error	101.754	184.557	109.839	109.445	184.557
	Bootstraps		169.505***	109.839	112.993	149.298***
Civil Status						
Married	Difference	744.340***	-169.014	312.334***	410.105***	317.018
	Std. Error	65.787	232.792	77.056	76.643	232.792
	Bootstraps		217.984	77.056***	82.862***	190.794
Not married	Difference	458.513***	291.366	198.650	291.918**	145.973
	Std. Error	111.856	269.513	123.716	123.347	269.513
	Bootstraps		175.65	123.716	123.901**	187.931
Residence						
Urban	Difference	601.921***	-241.530	267.280***	339.958***	296.238
	Std. Error	73.196	257.564	83.428	83.152	257.564
	Bootstraps		229.284	83.428***	86.728***	229.492
Rural	Difference	610.825***	533.894***	304.749***	431.930***	212.301
	Std. Error	87.402	194.422	89.944	89.325	194.422
	Bootstraps		199.236***	89.944***	103.051***	212.583**
Years of Education Attained						
Has at most 6 years of education	Difference	649.122***	519.413**	535.250***	625.116***	407.056*
	Std. Error	112.604	215.046	148.107	147.854	215.046
	Bootstraps		183.343***	148.107***	141.510***	194.598***
Has at most 10 years of education	Difference	260.729***	-199.001	-11.587	81.365	-40.327
	Std. Error	64.532	218.254	59.299	58.788	218.254
	Bootstraps		148.874	59.299	53.940	141.055

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Has at most 16 years of education	Difference	808.057***	-352.546	452.357***	512.350***	526.926
	Std. Error	102.890	348.942	117.571	117.237	348.942
			322.346	117.571***	121.736***	362.792
Has 17 or more years of education	Difference	194.439	-513.235	548.176	510.935	72.378
	Std. Error	970.838	2780.498	621.443	602.815	2780.498
	Bootstrap		1183.491	621.443	589.186	1169.306

*,**, *** indicate statistical significance at 10%, 5%, and 1% levels, respectively. The bootstrap standard errors are reported.

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To further the analysis of the ATT, we now examine the heterogenous effects of the demographic characteristics on the logarithmic values of the outcome variables. In tables 12 and 13, we see that males and those with lower education levels consistently show significant differences in income and food consumption. For instance, table 12 emphasizes the impact on farmer's income. The results show that those with at most 6 years of education show positive and most consistently significant differences in income. Table 13 reveals a similar trend where significant differences are seen across all matching algorithms for rural residents and farmers with low educational attainment. This time, however, we also see rural residents exhibiting significant gains in food consumption.

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Table 12. Heterogenous effects of demographic characteristics on the logarithmic values of farmer's income.

Demographics	Value	Unmatched	NN	KM	KM(0.1 bw)	LLR
Gender						
Male	Difference	0.273***	0.038	0.076***	0.119***	0.056
	Std. Error	0.208	0.063	0.021	0.021	0.063
	Bootstraps		0.044	0.020***	0.021***	0.0207**
Female	Difference	0.179***	0.159**	0.041	0.072**	0.058
	Std. Error	0.337	0.076	0.032	0.032	0.076
	Bootstraps		0.049***	0.027	0.027**	0.0284**
Civil Status						
Married	Difference	0.262***	0.039	0.065***	0.106***	0.067
	Std. Error	0.020	0.059	0.020	0.020	0.058
	Bootstraps		0.044	0.016***	0.018***	0.018***
Not married	Difference	0.187***	0.087	0.072*	0.109***	0.062
	Std. Error	0.038	0.088	0.038	0.038	0.088
	Bootstraps		0.048*	0.034*	0.032***	0. 028*
Residence						
Urban	Difference	0.182***	0.033	0.052*	0.081***	0.047
	Std. Error	0.020	0.061	0.021	0.021	0.061
	Bootstraps		0.050*	0.019**	0.020***	0.020**
Rural	Difference	0.282***	0.127*	0.098***	0.173***	0.035
	Std. Error	0.033	0.084	0.033	0.032	0.084
	Bootstraps		0.065**	0.033**	0.031***	0.034
Years of Education						
Has at most 6 years of education	Difference	0.308***	0.181*	0.245***	0.288***	0.190*
	Std. Error	0.042	0.101	0.047	0.046	0.101
	Bootstraps		0.084**	0.039***	0.039***	0.043***
Has at most 10 years of education	Difference	0.142***	0.028	0.020	0.057***	0.007
	Std. Error	0.024	0.066	0.021	0.021	0.066
	Bootstraps		0.042	0.019	0.016***	0.018

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Has at most 16 years of education	Difference	0.193***	0.023	0.052*	0.074***	0.081
	Std. Error	0.027	0.081	0.028	0.027	0.081
	Bootstraps		0.067	0.022**	0.024**	0.028**
Has 17 or more years of education	Difference	0.031	0.346	0.144	0.126	0.097
	Std. Error	0.178	0.387	0.138	0.135	0.387
	Bootstraps		0.235	0.152	0.151	0.136

*,**, *** indicate statistical significance at 10%, 5%, and 1% levels, respectively. The bootstrap standard errors are reported.

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Table 13. Heterogenous effects of demographic characteristics on the logarithmic values of farmer's food consumption.

Demographics	Value	Unmatched	NN	KM	KM(0.1 bw)	LLR
Gender						
Male	Difference	0.270***	0.028	0.118***	0.153***	0.098*
	Std. Error	0.018	0.056	0.018	0.018	0.056
	Bootstraps		0.040	0.017***	0.018***	0.016***
Female	Difference	0.139***	0.198***	0.041*	0.063**	0.053
	Std. Error	0.028	0.065	0.028	0.028	0.065
	Bootstraps		0.050***	0.027	0.025**	0.027**
Civil Status						
Married	Difference	0.237***	0.044	0.095***	0.126***	0.097*
	Std. Error	0.017	0.050	0.017	0.017	0.050
	Bootstraps		0.036	0.017***	0.015***	0.017***
Not married	Difference	0.190***	0.081	0.103***	0.133***	0.089
	Std. Error	0.032	0.078	0.032	0.032	0.078
	Bootstraps		0.058	0.031	0.028***	0.029**
Residence						
Urban	Difference	0.179***	0.027	0.075***	0.098***	0.076*
	Std. Error	0.018	0.057	0.018	0.018	0.057
	Bootstraps		0.035	0.017***	0.017***	0.020***
Rural	Difference	0.271***	0.200***	0.150***	0.198***	0.111*
	Std. Error	0.027	0.067	0.027	0.027	0.067
	Bootstraps		0.048***	0.022***	0.026***	0.024***
Years of Education						
Has at most 6 years of education	Difference	0.240***	0.096*	0.192***	0.226***	0.149**
	Std. Error	0.038	0.077	0.038	0.038	0.077
	Bootstraps		0.068	0.043***	0.019***	0.043***
Has at most 10 years of education	Difference	0.155***	-0.005	0.057***	0.088***	0.048
	Std. Error	0.021	0.062	0.021	0.021	0.062
	Bootstraps		0.039	0.019**	0.019***	0.021**

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Has at most 16 years of education	Difference	0.208***	0.010	0.099***	0.117***	0.118*
	Std. Error	0.023	0.073	0.023	0.023	0.073
	Bootstraps		0.053	0.026***	0.019***	0.022***
Has 17 or more years of education	Difference	0.207	0.155	0.277**	0.262**	0.210
	Std. Error	0.173	0.482	0.129	0.126	0.482
	Bootstraps		0.204	0.169	0.103*	0.113

*,**, *** indicate statistical significance at 10%, 5%, and 1% levels, respectively. The bootstrap standard errors are reported.

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Chapter 6: DISCUSSION

6.1. The effect of e-commerce selling participation on farmer's monthly income and food consumption

We identify the effect participation in e-commerce selling on farmer's monthly income and food consumption. From the unmatched data in table 8, we see that the farmers who participated in e-commerce selling had a mean income of Php. 25,796.35. This is higher than the non-participants by Php. 5,177.42 who only had Php. 21,276.14. In parallel, e-commerce participants had a mean monthly food consumption of Php. 2,558.26. This is higher than the non-participants by Php. 687.18 who only had Php. 2,645.49. So far, the results follow our expectations that e-commerce engagement leads to higher income and spending.

Although the unmatched data shows a large difference in average monthly income, it is substantially decreased in the other algorithms. It should be noted that it resulted in inconsistent significance levels. This implies that e-commerce selling may positively impact farmer's income but not as strong as initially observed. Meanwhile, average monthly food consumption also shows decreased difference with better significance levels across the four matching algorithms used. This suggests that impact of e-commerce on food consumption is more robust than its effect on income.

We address the inconsistencies by applying logarithmic transformation to our outcome variables (*ln_income* and *ln_consumption*). When we analyze the results in table 9, we further validate the positive impact of e-commerce participation. The unmatched data for average monthly income shows a difference of 0.247 at 1% significance level. This is

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supported by the various matching algorithms used except for NN. KM and LLR algorithms showing differences of 0.066 and 0.063, respectively, both significant at the 1% level. KM (0.1 bw) shows a significant difference of 0.106 at the 1% level. The same can be observed for average monthly food consumption where the unmatched data shows difference of 0.231 at 1% significance. This is followed by the matching algorithms used. NN shows a difference of 0.072 at the 5% significance level, and the KM and LLR show differences of 0.096 and 0.093, respectively, both significant at the 1% level. Lastly, KM (0.1 bw) indicates a significant difference of 0.072 at the 5% level.

The results show that after using the logarithmic values of the outcome variables (*ln_income* and *ln_consumption*), the values are more significant across most algorithms. Our findings are now more aligned with the related literature where e-commerce is positively related to income and food consumption. However, we must note that this also tells us that the effects of e-commerce selling are more prominent in farmer's food consumption than their income.

6.2. Factors affecting e-commerce selling engagement

First, we study the different factors that may influence a farmer to engage in e-commerce selling. The results in table 6 show this. Identifying the probability of an individual to decide helps policymakers and stakeholders develop appropriate interventions to promote e-commerce participation, which have been considered as an income-enhancing activity for the farmers. We analyze them one by one.

Many reports and studies have demonstrated how gender influences economic outcomes. Agriculture is not an exception. FAO (2011) reports that the differences in access

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to resources, social norms, and labor market opportunities can be attributed to gender. According to Doss (2014), there are gender disparities that are prominent in the agricultural sector that favor male farmers. These include access to credit, land, and technology, which ultimately affect productivity and household welfare. However, it seems to be the reverse in e-commerce participation. According to Albert *et al*., (2019), women are more likely to engage in e-commerce selling in developing countries, like the Philippines, because of the availability of flexible livelihood opportunities that can be done in the household. While mothers carry out their household responsibilities, online selling provides a viable economic opportunity to improve the family's income. Moreover, Hamayun *et al.,* (2023) reports e-commerce selling is an appropriate platform for women to participate in because they are more active in small-scale retail and handicrafts. E-commerce gives them access as it does not require significant capital investment or extensive supply chain marketing skills. They can take advantage of digital marketing which has become even more widely used since the pandemic. This made women in developing countries more adept in using various digital platforms for income generation, supported by government programs that target women empowerment in digital entrepreneurship. In contrast, Albert *et al.,* (2019) mentions that male farmers are less inclined to newer technologies, including digital marketing, as they often prefer traditional and larger-scale agricultural practices. These activities are often physical and direct, which can be tied to the traditional gender roles of older generations and rural societies.

Most of the Filipino farmers are ageing. From our filtered dataset, the average age of a farmer is 49 years old. Meanwhile, PSA (2020) reports that it is 57 years old. Either way, this poses a critical problem in the country's agricultural sector as most of them are nearing

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retirement age. Although quite small, we acquire a negative coefficient for variable *age*. This implies older farmers are less likely to participate in e-commerce selling. It is mentioned by the World Bank (2020) that older farmers are more inclined to traditional practices and are therefore more reluctant in employing new technologies. As for marketing, they often rely on contract growing or networking with local markets to sell their produce. Shifting to a digital platform will require a drastic change in the market and operations, discouraging older farmers. E-commerce is associated with uncertainties when faced with the combination of fluctuating online demand and perishable goods (Burton *et al.,* 2015). Coupled with their unwillingness to learn newer technologies, older farmers are even more likely to resort to dated marketing practices due to their risk aversion.

Our filtered data shows that 73.19% of the Filipino farmers are married. Orbeta (2005) reports that married households often have more stable incomes and better resource management. This is because they are encouraged to look for additional income streams to fulfill the household's higher financial needs. This allows them to pool their resources and labor to ease the financial burden. This could be combined with e-commerce, where the spouse who does not have physical or on-site work can sell produce online as an additional income source.

According to IFAD (2016), the economic disparity between access to markets, infrastructures, and services can be traced to the location of residence. People living in urban areas tend to have better access to education, healthcare, and employment opportunities. This is why e-commerce is more prominent among them. Conversely, those from rural areas face challenges in inadequate infrastructure, restricted market access, insufficient healthcare, technological access and lower quality of education. They report that there is a need to

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develop the rural communities to distribute economic growth throughout the country, thereby also decongesting the population in urban areas.

According to World Bank (2020), education level is important in adapting agricultural technologies among farmers. Additionally, they stated that educated farmers are more accepting of new agricultural technologies. However, the PSA (2020) reports that educational attainment is relatively low in the agricultural sector. This negatively affects their ability and confidence to engage economic opportunities such as e-commerce, seeing that it is a prerequisite in becoming proficient in using technology.

As mentioned, e-commerce is done with communications technology. Owning a personal computer and having internet connection provide participants an advantage through convenient access. Both enable the participation to the digital economy, thereby enhancing income and productivity. Additionally, they can potentially improve the farmer's communication and learning mode (OECD, 2015). In a related study, Aker (2010) concluded in his study that farmers become more reliant on mobile phones due to their affordability and portability. Having easier access to technology allows for better marketing communication, and even direct linkages. This could be maximized for income augmentation and better food consumption.

6.3. Sub-category analysis

Next, we do a sub-category analysis basing on the various matching algorithms while considering the propensity scores of the relevant demographic characteristics from tables 10 to 13. This helps us check the robustness of the results by analyzing how the demographic characteristics influence the impact of e-commerce on farmer's income and food

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consumption. For farmer's monthly income, we see that the values are significant across all matching algorithms for farmers who have low educational attainment. The values are also significant in all matching algorithms for farmer's monthly food consumption. This is followed by the farmers who live in rural areas, having significant values for all the matching algorithm except LLR. Using logarithmic functions on the two outcome variables (*ln_income* and *ln*_consumption), we see more significant differences across all matching algorithms and demographics but the most consistent remains to be rural residents and those with low educational attainment for both variables.

A comparable study by Wang, Chen, & Ding (2022) examined how the gap in farmer's expenditure can be eradicated by digital finance. The authors concluded with the findings that digital finance can ease the consumption inequality among farmers by stimulating e-commerce activities and alleviating income inequality. This proves that digital finance can be a tool in bridging the said gap. Moreover, they discovered that the effect was more prominent among farmers that are low-income and those that only have primary education in China. This relates to our study where the positive impact of e-commerce is more significant for farmers who have low educational attainment.

Furthermore, we identify that the farmers living in rural areas experience the positive effect of e-commerce selling. On a related study, Yin & Choi (2022) examined consumption gap using data from 27 provinces in China from 2002 to 2018 using both linear and panel threshold models. They concluded that a 1% rise in e-commerce engagement results to a 0.032% decrease in income gap. Moreover, they also found out that income-narrowing effect only took effects in regions with relatively low urbanization. This suggests that e-commerce can be used as a tool to narrow down the disparity between urban and rural income levels.

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Furthermore, they compared the values of the income-narrowing effect of the regions with lower and higher public expenditure and education levels. Accordingly, they investigated that the effect is much greater for the latter, implying that cities with low urbanization level will benefit with higher public expenditure and education levels in terms of income from e-commerce participation.

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Chapter 7: SUMMARY AND CONSLUSION

7.1. Conclusion

The study examines the potential of e-commerce in transforming the current economic conditions of Filipino farmers through analyzing the AWRS-APIS dataset using PSM. The study includes several demographic factors influencing e-commerce participation such as gender, age, marital status, location of residence, educational attainment and technological access. The analysis reveals that farmers who are young, women, married, and residents of urban areas are more likely to engage.

Next, the study analyzes the effect of e-commerce selling to the farmer's monthly income and food expenditure. The results show that participants experience improvement in their monthly income and food expenditure. However, we observe that the marginal effect is more robust on food expenditure as compared to monthly income. Then, we study the heterogenous effects of the demographic characteristics on how e-commerce influences the farmer's income and food consumption. We see that e-commerce participants with low educational attainment and living in rural residences receive greater marginal benefit from e-commerce participation in their income and spending in their food consumption.

These findings emphasize the potential of e-commerce as a tool to empower the smallholder farmers, which is consistent with several studies indicating that e-commerce has a positive effect on farmer's income and expenditure. This is the expected outcome because e-commerce is designed to eliminate intermediaries through direct transactions, thereby ensuring fairer price for agricultural produce and better income. This encourages entrepreneurial activities within the farms and farming households of the smallholder farmers (World Bank, 2020). The results aim to contribute to drafting programs and policies that

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appropriately target the involvement of farmers in e-commerce, ultimately contributing to the broader goals of sustainable agricultural development and poverty reduction in the Philippines.

7.2. Policy Recommendations

We now arrive at several policy implications that could be derived from the research outcome. First, we see that e-commerce holds the potential to improve farmer's income and food consumption. This gives the government an opportunity to invest on market digitalization and entrepreneurial literacy for farmers. Ang (2020) emphasized that there is a great need for market innovation for the agricultural sector, specifically on market digitalization. He added that it facilitates ease of market transactions and food supply acquisition for farmers to lower their marketing costs, resulting to better income.

Second, there should be provisions to support farmers in technological access. The World Bank (2020) reports that there are still many areas, especially those that live in remote locations, who do not have the technical know-how to take advantage of newer technologies. Meanwhile, there are already existing entrepreneurial literacy programs offered by different institutions such as the Department of Trade Industry, Department of Agriculture, related Local Government Unit offices, and NGOs. However, they must be more proactive ensuring their lasting effectiveness. A good example of this is the "*Bayanihan e-Konsulta*" launched by the former vice president of the Philippines, Hon. Leni Robredo. The program was intended as response to the Covid-19 pandemic to assist Filipinos. This included an online platform that for smallholder farmers to sell their products to consumers online. The products sold were then collected and delivered by displaced public utility vehicle drivers. The

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initiative contributed to addressing the disruption in the food supply chain while opening an income-generating opportunity for farmers and drivers (Cantal, 2021). Unfortunately, the program was discontinued after her term despite its effectiveness. This is the common practice in the Philippines, even at a local level. This calls for policies and programs that are designed for long-term implementation to sustain their impacts.

Third, the technical knowledge of the farmers should be improved through training and mentorship programs. This helps farmers to be more adaptive to newer technologies. This should be supplemented by encouraging the future generation to venture into innovative agricultural income-generating opportunities such as agricultural e-commerce. Integrating agriculture education with digital skills training will better equip the future farmers with navigate innovative agricultural ventures (World Bank, 2020).

Finally, smallholder farmers should be incentivized to participate in e-commerce selling. There are various business development programs that include e-commerce participation. One of the lead programs in the country is Digital PH by the Department of Trade Industry. The program promotes e-commerce and digitalization among micro, small, and medium enterprises (MSMEs). As of 2021, it was estimated that over a hundred thousand MSMEs participated in the program, boosting their digital presence which thereby resulted to an average of 30% revenue growth (DTI, 2022). Other programs include *Negosyo* Center E-commerce program, Go *Lokal*! Program, Youth Entrepreneurship Program, *Kapatid* Mentor ME Program, and *Pondo sa Pagbabago at Pag-asenso* or P3 Program. The reported benefits from these programs were growth in number of newly established businesses, e-commerce participation, and revenue. Proactively channeling these benefits to the country's

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smallholder farmers hold the potential to increase the farmer's income, thereby empowering local agriculture and food security.

7.3. Recommendations for Future Research

While the dataset referenced was comprehensive, there are more variables that could be considered to further narrow down the outcomes of the research. As mentioned in chapter 3, the dataset does not consider what goods these farmers sell in e-commerce platforms. Future research will benefit from data on products traded on e-commerce platforms. It is also mentioned in chapter 6 that farmers are more likely to depend on mobile phones. A dummy variable could be added to specify how it influences the likelihood of a farmer to engage in e-commerce. Moreover, the future research could expand the time period being studied. Remember that 2020 is the peak of the pandemic for many countries, including the Philippines. This may have affected several variables which may result in drastic changes than the norms.

The study used quantitative methods in assessing the impact of e-commerce on farmers. However, this may overlook the nuanced challenges faced by farmers in doing so. A qualitative approach could be added to evaluate existing policies and programs, focusing on how farmers perceive them. This mixed approach offers a more holistic overview of the integration of e-commerce in smallholder farmers. This could be integrated into the analysis using interviews and questionnaires to come up with a broader analysis.

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