Does Internet Usage Lead to An Increase in Household Incomes? Indonesian Rural Case Study

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Abstract

This study analyzes the effect of internet utilization on household income in rural Indonesia using Sakernas 2018 data. This research uses propensity score matching (PSM) to achieve the research objectives. The results show that the probabilities of using the internet are caused by family size, age of the head of the household, work experience, marital status, formal and informal education, experiencing severe difficulties in bodily functions, gender, business sector, and financial management. Furthermore, the study finds that the internet utilization increases household income in rural Indonesia by 29 percent.

Keywords: internet use; income; propensity score matching (PSM); household; rural Indonesia
JEL Classification: D31; O15; O18; O33

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1. Introduction

The ideal economic development requires a reduction in the level of inequality, including the gap between the development of urban and rural areas. It is known that the high inequality between urban and rural areas can cause widespread problems. As an illustration, currently, the poverty rate in rural areas (12,60 percent) exceeds urban areas (6,56 percent) (Central Bureau of Statistics [BPS], 2019). In addition, job opportunities in rural areas are also limited. On the other hand, rural communities view life in urban areas as more promising and offers more job opportunities. This will certainly encourage many rural communities to migrate to urban areas. If this is not addressed, then the level of population density in urban areas cannot be controlled and will actually cause negative effects that further exacerbate the situation, such as increasing unemployment and increasing crime rates.

Recent evidence reveals that there has been a drastic decline in the number of people living in rural areas in several developed and developing countries, including Indonesia. Some of the contributing factors are differences in the level of mastery of technology, dynamic social changes, and increasingly difficult economic problems (May et al., 2019).

If not addressed, the problems that arise are not only concentrated in urban areas, but this will also have an impact on a more serious problem, namely the decline in agricultural sector output (May et al., 2019). The migration of young people from rural areas to urban areas will cause rural resources to decrease drastically. In the end, agricultural products which are the main backbone of food security will be threatened.

Currently, the government and other stakeholders are trying to be able to provide solutions to these problems by accelerating economic development, especially in rural areas. One of the emerging solutions to accelerate rural development is through increasing access to information and communication technology (ICT). Several previous studies have identified the benefits of ICT access to improve economic performance through information transmission channels. As is known, increasing access to information will be able to reduce market failures caused by asymmetric information among economic actors (Stigler, 1961; Stiglitz, 1985). Information has economic value because it facilitates economic actors to make better economic decisions than in the absence of information. However, the characteristics of providing information are expensive or the information provided is sometimes incomplete. One reason is that in some cases we don't even know where the information we need is or is difficult to access.

Information and communication technology (ICT) which continues to develop is expected to be a solution to the problems mentioned above. ICT makes the provision and transmission of information easier and cheaper. The Internet, among other ICTs, has a special place as a source of information because of its ability to provide it at the lowest cost. For example, farmers in rural areas can use the internet to collect a lot of information about crop prices, crop sales trends, the most appropriate fertilizer and pest control, weather forecasts, and other related information, so that they can decide what crops to plant, when, where, and at what price they should sell their produce to optimize their income. To obtain this information, farmers do not have to go to the location of the information source. They can access it from anywhere as long as an internet connection is available, thus minimizing costs.

The Indonesian government has established several policies to encourage the provision of internet access for all Indonesians. In the context of equal distribution of internet access throughout Indonesia, the Ministry of Communication and Information has accelerated the distribution of internet access through the outputs of National Priorities for the ICT Infrastructure Provision Program, including the Palapa Ring, Base Transceiver Station (BTS), and Internet access at public service locations (Ministry of Communication and Information [Kominfo], 2020). The latest survey by the Agency for Research and Development of Human Resources, Ministry of Communication and Information of the Republic of Indonesia in 2017 showed that 32.5% of the rural population in Indonesia had subscribed to the Internet.

At the macro level, we can easily find studies on the relationship between Internet use and economic performance with various samples, methodologies, and data periods. For example, Choi & Yi (2009) have analyzed the effect of Internet use on economic growth in 207 countries in the period 1991 to 2000. Farhadi et al. (2012) using data from 2000 to 2009 from 159 countries, and Ariansyah (2018) used data from 2005–2016 from ASEAN countries to assess the relationship. All of these studies use GDP per capita as an endogenous variable and include Indonesia as one of the samples.

However, there are some criticisms of GDP per capita if it is used to capture people's welfare. First, GDP per capita only shows the average income and ignores the distribution of income. Second, GDP only captures transactions that have a market price and excludes informal transactions that may occur outside the market (Van den Bergh, 2009). Unfortunately, even since the first use of the Internet in the 1990s, it has been difficult to find national-scale studies on the impact of the Internet on the welfare of rural households in Indonesia. A study by Arifin (2011) found a positive effect of ICT on the welfare of Indonesian households. However, the study only looked at the impact of cell phone use.

Although we can access the internet through cell phones, especially smartphones, we cannot judge the impact of the internet through the influence of cell phones. One reason is that cell phones and the internet are from different waves of digital innovation. Cell phones are considered as the first wave of digital innovation, while the internet is classified as the second wave. Each wave has its own period that has an impact on social and economic development. Currently, the second wave has the greatest impact of any other wave, while the third wave (*internet of things*, robotics, artificial intelligence, and *machine learning*) will be in the next few years (Katz, 2017).

This study seeks to fill this gap by focusing on the role of the Internet in rural household incomes in Indonesia. More specifically, this study attempts to answer the following questions: Does Internet usage lead to an increase in rural household incomes?

In the next chapter, research methods will be described, followed by results and discussion, and will end with research conclusions.

2. Methodology

2.1. Data

This study uses secondary data from the National Labor Force Survey (Sakernas) for the period of August 2018. Sakernas is specifically designed to collect data that can describe the general state of employment between enumeration periods. The collection of employment data through Sakernas has three main objectives. The three objectives are to determine the characteristics of: (i.) working population; (ii.) Unemployment and underemployment; and (iii.) Residents included in the non-labor force category, namely, those who go to school, take care of the household and carry out other activities, apart from personal activities. The sample selected for the August 2018 Sakernas was 200,000 households with a document entry rate of 93.70 percent.

The Sakernas sampling framework takes into account the stratification of the census block business fields based on the 2010 population census (SP) in each district/city. This shows that Sakernas is specifically designed to estimate employment indicators, in contrast to the basic sample frame used in other surveys/censuses that also collect employment data, such as SP, Supas and Susenas.

The concept and definition used in the collection of employment data by the Central Bureau of Statistics is *The Labor Force Concept* recommended by the *International Labor Organization* (ILO). This concept divides the population into two groups, namely the working age population and the non-working age population. Furthermore, the working age population is also divided into two groups based on the main activities they are currently doing. The group is the Labor Force and Not the Labor Force.

2.2. Variable Operational Definition

After the sample and unit of analysis have been determined, the next step is to establish the variables according to the relevant definitions. The formation and operational definitions of variables can be seen in Table 1.

2.3. Analysis Method

The purpose of this study was to determine the relationship between internet use and household income in rural Indonesia.

Table 1: Definition and Description of the Data of the Variables in the Model

Variable	Description
Outcome	
Income	Income, basic wage/salary and allowances received by the head of household (HH) for a month.
Treatment	
Internet	(dummy) 1=accessing the internet for work purposes, 0=other
Covariates	
Family size	Number of family members
Age	Age of head of household (HH)
Experience	Years worked
Marital status	(dummy) 1= married; 0=other
Education	(dummy) 1=HH with minimum junior high school diploma, 0 = other
Course	(dummy) 1= HH has received training/courses/training and obtaining a certificate, 0 = other
Migration	(dummy) 1= district/city of current head of household is different from place of birth, 0=other
Severe Difficulty/Disorder	(dummy) 1= HH has severe difficulty/impairment in one of the vision, hearing, mobility, finger/hand movement, speech/communication, and other difficulties; 0=other
Gender	(dummy) 1=male; 0=girl
Agricultural Business Field	(dummy) 1=HH works in the agricultural business field; 0=other
Financial Management	(dummy) 1=Place of work performing financial management; 0=other

Source: Author, processed from Sakernas (2018)

Researchers assume that some households may choose their own decision-making, to use the internet, this can lead to selection bias in some sample households (Alene & Manyong, 2007; Tesfaye & Tirivayi, 2018; Deng et al., 2019).

The decision of the head of household to use the internet or not may be a conscious effort. For example, some household heads consciously want to increase agricultural productivity by using the internet and thereby increase their household income. On the other hand, other household heads may decide not to use the internet to increase their agricultural productivity, but may use other methods to do so. Thus, internet users will systematically differ from non-internet users.

The above conditions make the status of internet use as endogenous, and therefore, the use of econometric methods other than *ordinary least squares* (OLS) is needed to avoid estimation bias problems. One of the appropriate methods to be used to avoid this problem is to use the propensity score matching (PSM) method. Propensity Score Matching (PSM), defined as a non-parametric approach used to find a comparison group from the *selected non-treated* (non-intervention) group, so that the observed characteristics of the selected group (*selected group*) will be similar to those of the intervention group (*treatment groups*). The two groups were then matched based on their respective *propensity scores*.

2.3.1. Propensity Score Matching (PSM) Model

The main objective of this model consists of intervening on the outcome and controlling the respondent 's *outcome*. The equation can be written as follows:

$$Y_i = D_i Y_{1i} + (1 + D_{i_i})Y_{0i} \tag{1}$$

The above equation shows $D_i\{0, 1\}$ is an indicator of *treatment variable*. D_i is 1 for *the treatment group*, that is, if the head of the household uses the internet for work purposes, 0 is anything else. Y_i is the *potential outcome* of household i. $Y_{1i} = 1$ is the *potential outcome* of *the treatment group*, namely the head of the household who uses the internet for his work. On the other hand, $Y_{0i} = 0$ is the *potential outcome* of *the control group*, namely household i without internet use. *Treatment effects on the treat* (TOT) for households can be written as follows:

$$I_\iota = Y_{1i} Y_{0i} \tag{2}$$

The fundamental problem that causes counterfactual problems is that it is not possible to observe the *potential outcomes* of *the treatment group* (Y_{1i}) and *control group* (Y_{0i}) at the same time. Therefore, there is only one *potential outcome* for each observed household, so the *estimated effect* of the *treatment effect* is considered impossible. This study uses *the average treatment effect on the treat* (ATT) to estimate the average household *outcome with the use of the internet for work purposes*. ATT can be written as follows (Cameron & Trivedi, 2010):

$$ATT = E[\Delta | D_i = 1] \tag{3}$$

$$ATT = Y_{1i} Y_{0i} + E[Y_1 Y_0], D_{i_i} = 1 \tag{4}$$

$E[Y_{1i}, D_{i_i} = 1]$ is the *potential outcome* of households using the internet for work purposes and is considered potentially observable. The observation $E[Y_{0i}, D_{i_i} = 1]$ is a *potential outcome* for those who do not use the internet and cannot be observed because it is a missing counterfactual. To calculate ATT, we must find the substitution for $E[Y_{1i}, D_{i_i} = 1]$. One thing that might be done is to take advantage of the *potential outcome* of households without internet use for $E[Y_{0i}, D_{i_i} = 0]$. Since the *potential outcome* of household use of the Internet for work is $[Y_{0i}, D_{i_i} = 1]$ and was not observed in the same period when the respondent received treatment, the ATT can be assumed as:

$$ATT = E[Y_{1i}, D_{i_i} = 1] E[Y_{0i}, D_{i_i} = 0] \tag{5}$$

At this stage, ATT is the result of the average selection bias, which is the difference between the *potential outcome* of households using the internet $[Y_{1i}, D_{i_i} = 1]$ and the *potential outcome* of households not using the internet $[Y_{0i}, D_{i_i} = 0]$.

3. Result and Discussion

In the results and discussion chapter, we will explain descriptive analysis, the probability of households using the internet for their work, and see how the income difference between household heads (HH) who use the internet in their work and those who do not use the internet at work will be explained.

3.1. Descriptive Analysis

The descriptive statistics of this study are shown in Table 2. The unit of analysis of this research is the head of household (HH) in rural Indonesia. Table 2 shows a summary of descriptive statistics for a sample of 102,433 HHs from the entire population of HHs in rural areas throughout Indonesia. The results revealed that the average monthly income of household heads in rural Indonesia is IDR517,892.6. Furthermore, it is known that only 5 percent of household heads in rural areas use the internet for their work purposes. This shows that the use of the internet for productive activities is still very small for household heads in rural areas. This could be because internet access to rural areas is still relatively low, or it could be because rural communities do not yet know how to use the internet for productive purposes (Subiakto, 2013). Table 2 also shows that the average number of household members in rural Indonesia is 4 people, with the average age of the head of household being almost 50 years. This also shows that the HH population in rural areas is quite old.

Furthermore, it can be seen that in general, household heads in rural Indonesia have long experience in their field of work, with an average number of years working for almost 12 years. Table 2 also shows the education level of rural household heads in Indonesia, it is noted that only an average of 20 percent of household heads have graduated from basic education in Indonesia. This proves that the education level of head of household in rural Indonesia is still quite low, even that only 20 percent of those who pass basic education have graduated. In addition, not many household heads in rural areas have attended the course, which is only 6 percent of the total population on average.

Finally, what can be *highlighted* from Table 2 is that most of the livelihoods of household heads in rural Indonesia are in the agricultural sector, with a percentage of 53 percent, and the majority of household heads are male with a proportion of 85 percent.

3.2. Probability of Households in Using the Internet for Their Work

Table 3 is the result of the probit regression model regarding the probability of household heads in using the internet for their work purposes. From the table it can be seen that all variables used in this study have a significant influence on the probability of internet use by household heads, which are influenced by family size, age of household head, household head experience, household

Table 2: Descriptive Statistics

Variable	Obs	mean	Std. Dev.	Min	Max
Outcome					
Income	102433	517892.60	1370977.00	0	30000000
Treatent					
Internet	102433	0.05	0.22	0	1
Covariates					
Family size	102433	3.74	1.66	1	22
Age	102433	49.55	13.28	15	98
Experience	102433	11.88	11.90	0	74
Marital status	102433	0.81	0.39	0	1
Education	102433	0.20	0.40	0	1
Course	102433	0.06	0.23	0	1
Migration	102433	0.19	0.39	0	1
Severe Difficulty/Disorder	102433	0.02	0.14	0	1
Gender	102433	0.85	0.35	0	1
Agricultural Business Field	102433	0.53	0.50	0	1
Financial Management	102433	0.21	0.41	0	1

household marital status, household education education, courses by household head, household migration migration, Difficulties/Severe Disturbances by HH, Gender of HH, HH Agricultural Business Fields, and Financial Management of HH.

Table 3: Probability of Internet Usage with Probit Model

Dependent Variable Internet	coef.	Std. Err.
Family size	-0.053***	0.012
Age	-0.043***	0.002
Experience	0.025***	0.002
Marital status	0.297***	0.079
Education	1,204***	0.037
Course	0.832***	0.041
Migration	0.158***	0.037
Severe Difficulty/Disorder	-1.374***	0.421
Gender	0.311***	0.088
Agricultural Business Field	-1.716***	0.055
Financial Management	1.655***	0.039
constant	-2.620***	0.112
Number of Obs	102,433	
Wald chi2(12)	13,570.93	
Prob > chi2	0.0000	
Pseudo R2	0.3357	

Note: *** is significant at the 1 percent alpha level.

An interesting result was found that the use of the internet for work purposes by household heads tends to be greater in younger household heads. The younger the age of the head of the household, the more likely the household is to use the internet in their work.

Next, the results that also need to be considered are the variable difficulty/severe interference in the household head towards the probability of using the internet for work. Table 3 shows that household heads with severe visual, hearing, and other impairments have a lower probability of using the internet for their work. This indicates that household heads who have severe disabilities have difficulty getting internet access or may also have difficulty using the existing internet.

Furthermore, from Table 3 it can also be seen that education and courses which are variables that indicate a person's level of *knowledge* and *skills* are directly proportional to the likelihood of head of household using the internet in their work matters. This shows that household heads who have educational credentials and courses understand that the internet can provide benefits in their work affairs.

Then, in contrast to Rini & Rahadiantino (2020) who proved that there is no difference between female and male head of household in terms of the probability of using the internet in their work, this study shows something different. This is possible because the characteristics of the business fields that are used as research objects are very different in characteristics. Rini & Rahadiantino (2020) used a sample of small and medium-sized enterprises (SMEs) in using the internet for their businesses. It can be seen that for business activities, in this case SMEs, business actors, both women and men, have high exposure to internet use and do not have a significant difference. This is different from the characteristics of work in rural Indonesia which is still dominant in the agricultural business field, where in this business field, male household heads are more dominated, then male household heads also use the internet more for their work than female household heads.

3.3. The Impact of Internet Use on Household Income in Rural Indonesia

Before discussing the estimation results, it is necessary to look at the *propensity score match* of the covariates between observations in the control group (*control group*) and observations in the *treatment group* (*treatment group*). This is to ensure that the observations used in the estimation are in accordance with the procedure.

One indicator that can be used is by looking at the mean (*mean*) percentage of the bias between covariate observations, namely between the observations of *the control group* and *the treatment group* (Rosenbaum & Rubin, 1985). Table 4 shows the percentage of covariate bias between *the control group* and *treatment group observations*.

Based on Table 4, it can be seen that the average percentage (*mean*) *of the bias between the control group* and *treatment group* covariates was 3.2. Although there is no definite indicator of what percentage of bias is tolerated as a good fit, previous studies, such as Sianesi (2004) and Caliendo et al. (2005), explain that the average level of tolerable bias is below 5 percent. Thus, the sample of covariate observations between *the control group* and the *treatment group* used in

Table 4: Evaluating Matching Quality Evaluation: Percentage of Covariate Bias between Observation Control Group and Treatment Group

Variable	%Bias
Family size	-0.8
Age	5
Experience	4.3
Marital status	-4
Education	5.6
Course	5.7
Migration	2
Severe Difficulty/Disorder	0
Gender	-3.8
Agricultural Business Field	2.7
Financial Management	-1.2
Mean Bias	3.2

this study was in accordance with the procedure in the estimation of *propensity score matching*.

Furthermore, Table 5 shows the results of the estimated *average treatment effect on the treated group* (ATT) using the PSM method, which reveals the impact of internet use on household income in rural Indonesia. By using ATT PSM, the estimation results have corrected the selection bias between *observable* and *unobservable factors*. Table 4 shows that the use of the internet by the head of household in rural Indonesia has increased household income by 29 percent.

Table 5: Impact of Internet Use on Household Income in Rural Indonesia: Average Treatment Effect on the Treated Group (ATT) Using the Propensity Score Matching (PSM) Method

	Mean Outcome					
Outcome Variable	User	Not User	ATT	SE	T-stat	Change
Income	2,518,497	1,953,324	565,173	58.026	9.74***	29%

Note: *** is significant at the 1 percent alpha level.

Of course, there are several reasons why household heads who use the internet in their work have higher incomes than those who do not use the internet. For example, for farmers, as the largest employment in rural areas, they can use the internet to collect a lot of information on crop prices, crop sales trends, the most appropriate fertilizer and pest control, weather forecasts, and other related information, so that they can decide what crops to plant. will be planted, when, where, and at what price they should sell their crops to optimize their income. To obtain this information, farmers do not have to go to the location of the information source. They can access it from anywhere as long as an internet connection is available, thus minimizing costs.

4. Conclusion

This study analyzes the effect of internet use on household income in rural Indonesia using the 2018 Sakernas data. The unit of analysis of this research is the head of household (HH) in rural Indonesia with a total sample of 102,433 HH from the entire population of HH in rural areas throughout Indonesia. The results revealed that the average monthly income of household heads in rural Indonesia is IDR517,892.6. Furthermore, it is known that only 5 percent of household heads in rural areas use the internet for their work purposes.

study uses a propensity score matching (PSM) and probit model to achieve the research objectives. The estimation results show that the probability of internet use is influenced by family size, age of the head of the household, experience in work, marital status, formal and informal education, migration, having severe difficulties/disorders in bodily functions, gender, business field, and financial management. Furthermore, the study found that internet use increased household income in rural Indonesia by 29 percent.

The results of this study provide concrete evidence that access to the internet is needed to increase people's income, especially those in rural areas. It is hoped that in the future more and more rural communities will be able to access the internet and use it for all their needs, especially for things that are productive, so that in the end it will be able to improve the welfare of the community.

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