The Role of Mobile Phone and Internet Use in the Performance of Rural Non-Farm Enterprises: An Analysis of Indonesian Rural Households

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ABSTRACT

Rural non-farm enterprises have an increasingly important role in economic development in developing countries. The performance of rural non-farm enterprisess is expected to continue to improve in line with the use of telecommunications technology in their business. Such improvement resulted from the use of communication technologies such as mobile phones and internet that are able to reduce information search and expand market information. This study analyzes the role of mobile phone and internet use in the performance of rural non-farm enterprises. By using household-level data from the Fifth Wave of the Indonesian family life survey (IFLS 5) in 2014 and applying the propensity score matching method, the study found that the use of mobile phones and the internet has a positive impact on the performance of rural non-farm household enterprisess. It shows that the telecommunications infrastructure development policy in rural areas is able to provide economic improvement for rural households.

1. Introduction

Rural areas are the main areas for the agricultural sector activities. Nevertheless, the rural non-farm sector, especially in developing countries has been increasingly attracting attention. This was seen during the 1997 financial crisis, where the Rural Non-Farm Economy (RNFE) was able to stabilize the incomes of the rural poor, coupled with the fact that this small-scale industry was able to perform better during the crisis when compared to large scale industries (Tambunan, 2000). A comprehensive study of rural non-farm enterprises (RNFEs) has been conducted by Lanjouw and Lanjouw (1999). This study defines the non-farm sector as a sector that includes all economic activities except agriculture, animal husbandry, fisheries, and hunting. The scope of the non-farm sector in this study follows the definition of the Statistics Indonesia (BPS), which covers businesses in the mining and quarrying, industry, electricity, gas and water sectors; construction sector; trade sector; transport, storage, and communications sectors; financial, insurance, real estate, renting, land, and business service sectors; other community, social and personal services sectors. The non-farm sector is a very heterogeneous sector because it is negatively defined as non-agriculture. Generally, people with great capitals are able to diversify their business into the non-farm sector. This sector develops along with the increasing number of skilled population, both in urban and rural areas. In addition, with the decreased labour absorption capacity of subsistence agriculture (Abey, Booth & Sundrum, 1981) and the scarcity of land for agriculture, it is necessary that non-farm businesses, especially in rural areas be promoted.

In the last few years, rural non-farm employment has also been emphasized as a potential escape from poverty for those who failed to earn income from the agriculture (Cherdchuchai & Otsuka, 2006; McCulloch, Weisbrod, & Timmer, 2007). This condition is also reflected in the pattern of labor absorbtion in Indonesia. Although the workforce in rural areas is still dominated by the agricultural sector, the trend has decreased compared to the manufacturing and services sectors. One of the main advantages non-farm sector of activities is risk diversification (Barrett, Reardon & Webb, 2001) and additional sources of income given that wage employment in this sector is able to contribute around 30-50% to rural household income (Reardon, 1997;

Berdegue, Reardon, & Escobar, 2001; Escobal, 2001; Lanjouw & Lanjouw, 2001). Abey, Booth, and Sundrum (1981) found that the main reason for the growth of the rural non-farm sector economic activities was the low absorption of labor in the agricultural sector. The diversification of businesses into this sector (see figure 1) shows that the non-farm business sector is increasingly needed to support job creation, especially in rural areas. Although the scale of rural non-farm enterprises in general is still in the scale of household enterprises with a workforce of one or two people, but their sufficiently large number makes the potential for employment absorption respectively large. In addition, non-farm businesses also have a positive impact on the increase of rural household incomes.

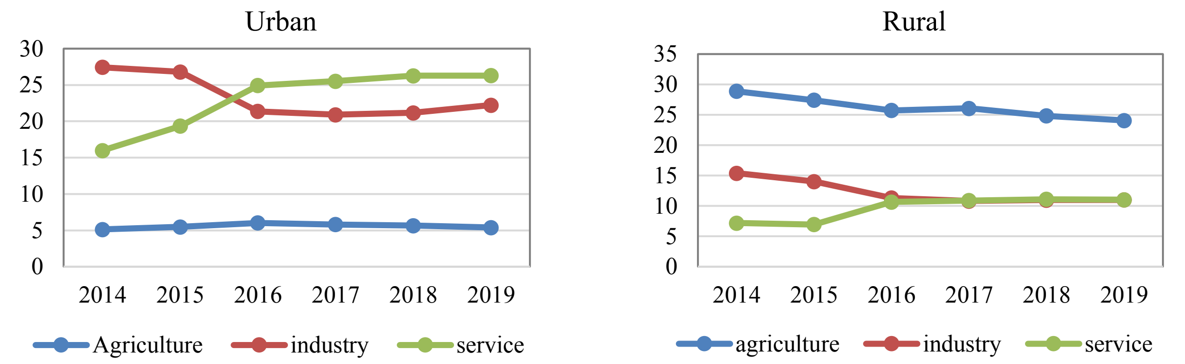

Figure 1. Distribution of population of 15 Years and above working by Major Industry and Region (in %)
Source: Publication of Indonesian employment as of August 2014 – February 2019 – Statistics Indonesia (BPS) (data has been reprocessed)

One of the factors indicated as a key driver of the non-farm sector is the availability and quality of telecommunications infrastructure. The availability of quality telecommunications infrastructure can facilitate the flow of information to support marketing and access to raw materials (Fafchamps, 1992). Investment in the construction of mobile telephone and internet network infrastructure, often referred to as interventions that can help the rural non-farm sector economic activities because it is able to reduce transaction costs (Hengst & Sol, 2001). The availability and quality of mobile telephone infrastructure can increase the use of cell phones to communicate (making phone calls, sending texts, and access communications and other information using certain applications). This mobile technology can be accessed by most of the population because using mobile phones only requires simple basic literacy. Lack of transport infrastructure, low levels of education, and migrant-labor-dominated workforce are some of the characteristics of rural areas that emphasize the need for real-time voice communication that can be catered by mobile phones. For example, mobile phones play a role in finding sources of information about input market such as raw materials (Arifin, 2012; Ogutu, Okello & Otieno, 2014) without having to go to the market. In addition, with the flexibility and quality of real time voice communication provided by mobile phones, businesses can communicate (both by voice and text) with their potential customers not only within the area around the business location, but also with consumers from outside their village areas with a faster market response (Frempong, 2009; Donner, 2006).

Meanwhile, internet access (via both mobile broadband and fixed broadband) also plays a role in improving the rural economy. The use of the internet is able to facilitate the provision, transmission, and manipulation of information of both audio and visual so that internet communication (whether accessed via a smartphone or a computer) is better than telephone communication which can only be done through voice or text. With the internet that can be accessed through a smartphone, other forms of communication such as pictures and videos become easier to have anywhere and at any time.

Today, the use of the internet for business has been developing, from electronic information exchanges to the use of applications of business strategy, such as marketing, sales, and customer service. The internet supports communication and cooperation between employees, consumers, sellers, and other business partners so that people from different locations work together as a virtual team to develop, produce, market and maintain products or services. With the internet, business actors no longer have difficulty in obtaining any information and anywhere to support their business activities as long as an internet connection is available.

However, on the other hand, the increasingly advanced development of facilities can also pose a threat to the development of rural non-farm enterprises. With more developed rural infrastructure, access to rural areas will be more open and allow city products to compete with rural non-farm enterprises products so that protection against non-tradability will be increasingly eroded (Start, 2001). Furthermore, according to Malecki (2003), infrastructure such as telecommunications technology is only one of the small (insignificant) factors that play a role in rural development. The main affecting factor is the quality of local human capital. Thus, the development of telecommunications infrastructure to increase the use of mobile telephones and the internet for rural residents can have both positive and negative impacts on the performance of rural non-farm enterprises.

The relationship between telecommunications infrastructure and the economy of the rural non-farm sector has been widely discussed in many literatures, especially in developing countries. The studies are mostly carried out in Latin American countries, Sub-Saharan Africa, and Asia, including in Indonesia. However, as previously explained, these studies have varied results. To test this ambivalence, this study is focused in developing countries in the Asian region, especially Indonesia. Indonesia itself is a developing state in a form of an archipelago, making interaction between regions or between villages, especially those between different islands, has relatively high costs. In addition, high population density is also potential to give different results, given that a large population will encourage a wider market. In this context, the use of mobile telephones and the internet is expected to increase business efficiency.

An analysis of the effect of telephone use on non-farm household poverty has been carried out in Ghana (Danqueh, 2008). Related studies have also been carried out in Indonesia including Ariyansyah (2018) who analyzed the influence of the internet on the welfare of village households, and Arifin (2012) who analyzed the influence of mobile phones on household welfare. Both studies have only analyzed the impact of mobile telephone and/or internet usage on the welfare of rural households in general and have not specifically analyzed the impact on rural non-farm households. In order to find out the importance of non-farm households economic activities and the use of mobile phones or the internet to the development of rural areas, it is necessary to conduct a study that focuses on the role of mobile phones or the internet on the performance of rural non-farm enterprises. This study aims to analyze the simultaneous use of the internet and mobile phones using household-level data of rural non-farm enterprises. Furthermore, this study also aims to examine if mobile phone use or internet use makes the most contribution to the improvement of rural non-farm enterprises in Indonesia.

2. Literature Review

2.1. Theoretical Foundation

Referring to Lanjouw and Lanjouw (1999), rural non-farm entrepreneurship is defined as being all those work activities in the industrial, manufacturing, and service sectors carried out by people living in areas with population densities below certain thresholds that define the area as rural areas. Meanwhile, the definition of rural areas used in this study refers to the definition by the Statistics Indonesia (BPS). The said criteria are related to population density, percentage of agricultural households, and the number of urban facilities, formal education facilities, public health facilities, and the like. As for the criteria of urban (2000), 3 indicators are used, namely: population density per km^2, percentage of agricultural households, and access to reach urban facilities. From these 3 indicators, the score limit for a village to be included in the category of urban villages is ≥ 10.

Unlike urban non-farm enterprises, business units in rural non-farm enterprises sector tend to have low productivity with a limited ratio of capital and labor. Rijkers, Laderchi, and Teal (2010) found that the output ratio per workforce for remote rural companies is 0.43 while for urban companies is 2.30. In addition to capital investments that mostly rely on personal savings, these small-scale entrepreneurs also generally have limited access to information about markets, new technologies, and trends related to consumer preferences. Meanwhile, information is a key component for economic agents in making optimal decisions.

In the micro context, penetration of Information and Communication Technology (ICT) devices, such as mobile phones and the internet, creates greater opportunities to gain skills and knowledge. For example, those who can use internet technology, in certain workplace, have the opportunity to put on better and more efficient performance than those who cannot. In the human capital theory, investing in human capital is able to encourage someone's productivity which in turn will increase their income. Likewise, the application of ICT in companies is able to encourage internal processes in an organization to be more efficient and effective, shorten coordination chain, and ultimately reduce coordination costs (Hengst & Sol, 2001). This will encourage companies to operate more efficiently and maintain their superiority through the management and improvement of information technology. This can ultimately improve company’s performance and labor income.

In addition, productivity is not only reflected by how efficiently inputs are transformed, but also how well information is applied in resource allocation decisions. Information has an important role in improving economic performance because of its ability to reduce the risk of market failure caused by asymmetric information between economic agents (Stigler, 1961). Conceptually, as it was mentioned by Ronald Coase (1937), the total costs are not merely made up of the sum of production costs, but also the costs required to conduct transactions, including the cost of information retrieval. Referring to the Transaction Cost Economy (TCE) proposed by Coase (1937), the general components of transaction costs include information retrieval costs, negotiation costs, and contract enforcement costs. Information costs incurred before transaction occurs, the transaction can be in the form of costs to identify potential trading partners, to obtain market price information, and to retrieve potential competitor information. ICT can facilitate economic agents in obtaining information so as to reduce the cost of information that arises. The lower the cost of information, the lower the transaction costs, which in turn will lead to increased revenue.

2.2. Previous Research

Several cross-country studies have found positive and significant effects of the influence of telecommunications infrastructure on economic growth. Roller and Waverman (2001) discussed the two-way causality between investment in telecommunications infrastructure and the economic performance of 21 OECD countries over the 1970-1990 period. The study used a micro-model of supply and demand for telecommunications investment. This model estimated changes in telecommunications infrastructure stock and its relationship with telecommunications investment to anticipate endogeneity of telecommunications investment. This study found that there is a a positive causal link between telecommunications infrastructure with aggregate output, the higher the development of telecommunications infrastructure, the higher the economic growth in OECD countries. Similar finding was also found by Shridar and Shridar (2004) who used the Roller and Waverman (2001) framework in 63 developing countries in their research. Mobile telephones and fixed-line telephones were used as proxies for telecommunications and the 3SLS model was used to build equations wich endogenizes the economic growth and penetration of telecommunications. The study found that telecommunications penetration significantly affects economic growth.

Furthermore, micro-level research investigating the effects of telecommunications has also been carried out. Michael Danqueh (2018) investigated the effect of mobile phone access on the welfare of non-farm enterprises households in Ghana. Considering the problem of endogeneity and the nature of binary dependent and independent variables, the study used a bivariate probit equation model. Research findings show that ownership of telecommunications access increases the likelihood that households be free from poverty by 15%. This shows that telephone access has a positive impact in accelerating non-farm enterprises business activities which subsequently leads to higher sales revenue. Furthermore, the findings show that the mobile phone access has a significant effect only on the welfare of rural non-farm households, and not on urban non-farm households. However, estimates of sales of non-farm enterprises have a significant effect on both rural and urban households.

Labonne and Chase (2009) tried to analyze the impact of information technology on the welfare of farmers in developing countries. Using panel data in 2003 and 2006 in a number of poor areas in the Philippines, estimates were made for changes in consumption as a result of mobile phone ownership. Strategy IV (instrumental Variable) was used to overcome endogeneity trend in the model, by using information on the availability of mobile telephones at the village level as well as the highest level of education achieved by children in families who attend school. The study found that mobile phone ownership had a positive impact on the per capita consumption growth rate of 11-17%.

Furthermore, Tankari (2018) estimated mobile phone ownership to household poverty as reflected by the total per capita expenditure ratio, i.e. total expenditure per capita divided by the poverty line. Indications of endogeneity in the model were anticipated by IV which exploited exogenous variables at the community level, namely: the proportion of household heads who can read multiple languages, radio services in the community, and the distance between the community center and the administrative center. The results concluded that the number of mobile phones had a positive impact on household welfare. Total mobile phone ownership increased 54.2% of household consumption per capita ratio. Meanwhile, Issahaku, Abu, & Nkegbe (2018) evaluated the impact of mobile technology on agricultural productivity in Ghana. To overcome selectivity bias, the estimation used was the Propensity Score Matching (PSM) method. The results showed that the ownership and use of mobile phones significantly increase agricultural productivity in Ghana. In addition, to test the consistency of the results, the Heckman-Selection method was also used in estimating the effect of ownership and use of mobile phone. Consistent results are shown from both methods.

In addition, several studies used the internet to reflect ICT infrastructure and its effects on the welfare of rural households. Ariyansyah (2018) analyzed the relationship of internet penetration using cross sectional Indonesian national survey data in 2016. The study showed a positive impact on household monthly income due to internet penetration. Litan and Rivlin (2001) argued that the internet impacts business productivity by reducing transaction costs, especially in the production and distribution of goods and services and is able to improve management efficiency with its ability to shorten the coordination chain.

However, some empirical literature found that telecommunications technology have insignificant impact on economic growth, especially in rural areas. As stated by Hudson and Parker (1990) that there are three factors which caused the insignificant effect of technology application in rural areas, namely lower population density, the distance between the rural communities from urban centers, and economic specialization only in sectors other than information or knowledge. This is supported by Malecki (2003) who argued that telecommunications infrastructure has only a small effect on village development if it is not accompanied by an increase in the quality of human capital in the region itself. In addition, Dasgupta, Sarkis, and Talluri (1999) suggested that when an enterprise is invested in communication technology there will be a greater need for coordination. Meanwhile, access to communication technology is relatively more expensive in rural areas due to limited telecommunications infrastructure, which leads to potentially higher costs compared to benefits.

3. Research Method

3.1. Data and Variabels

The data used in this study is taken form Fifth Wave of the Indonesian family life survey (IFLS 5) which was conducted in mid-2014 to early 2015 (Strauss et al., 2016). This survey included a national random sample of 15,921 households. This data was chosen as a sample because it contains comprehensive information related to business activities in the non-agricultural and agricultural sectors, household demographic characteristics, and infrastructure characteristics in an area. Data used in this study is cross-sectional data sets. This study focuses on households that operate non-farm enterprises within areas that are categorized as rural. Of the total 15,921 households surveyed, 6,339 households were in rural areas. Out of

6,339 households, only 2,111 have non-farm enterprises, but only 1,422 households have information related to village infrastructure.

In analyzing the influence of information and communication technology infrastructure on the development of rural non-farm enterprises, this study will oversee the impact of the use of ICTs in non-farm economy on business performance as measured by business profits. Business profit is measured by the net income received from non-farm enterprises. The main explanatory variable in this research is the use of dichotomous technology. The variable use of technology will be seen from two devices, namely mobile phone use and internet use in non-farm enterprises. The telephone in this study is mobile phones used by business actors for their non-farm enterprises needs, while the internet in this study is internet connection in general regardless its type of connection/technology, which is used and functioned for non-farm enterprises needs. Furthermore, to see household participation in using mobile phones or the internet, several control variables are used such as household characteristics (Leung & Wei, 1998), NFE business characteristics (Dholakia, Dholakia & Della, 1991), as well as regional and infrastructure characteristics as shown in Table 1.

Table 1. Research Variable Specification

Variable		Specification
Variabel Outcome		
RNFE Activities	NFE Performance	Net income from non-farm economy
Interest Variable		
ICT Device	Mobile phone	Dummy use of mobile phones in business; 1 if the household uses a cell phone, and 0 for the other.
	Internet	Dummy use of the internet in business; 1 if the household uses the internet, and 0 for others.
Control Variable		
Characteristics of Head of Household	Age	Age of head of household
	Gender	*Dummy* gender; 1 for male, and 0 for the other
	Occupation	Dummy main job of head of household; 1 if working in the formal sector, and 0 for others
	Education	Year of school attendance of head of household
Characteristics of Household	landfarm	Dummy landfarm ownership by households; 1 for ownership, and 0 for others
		There is one household member who manages businesses in the agricultural sector
	Electricity	Dummy access to electricity; 1 for household electricity consumption> 0, and 0 for others
Characteristics of Non-farm Enterprise	Owner	*Dummy* enterprise ownership; 1 if the enterprise is fully owned by household; and 0 for others
	Worker	Number of workers in NFE (paid or not paid)
	NFE_Services	*Dummy* types of business; 1 if business in the service sector and 0 for others
	NFE_year	Years of business running
Characteristics of area	Java	Dummy business location; 1 if the business is located in Java, and 0 for others
	Intensity of Blackout	The intensity of blackout (PLN) in the village; 1 if a blackout occurs at least once a week, and 0 for others (no blackouts in one week)
	Speed	The average speed to access public facilities available in the village
	Signal strength	Number of BTS per 1 million population in one province

3.2. Theoretical Model

As previously explained, this research will examine the effect of internet and mobile phone use on the performance of rural non-farm enterprises. Furthermore, this study aims to examine if mobile phone use or internet use contributes the most to the improvement of rural non-farm enterprises in Indonesia. Theoretically, business in any sector is always oriented to profit maximization (Nicholson, 1998). Therefore, in measuring the performance of rural non-farm enterprises, this study will use the level of profits obtained by rural non-farm enterprises as a performance measure.

In economic theory, profit (denoted by π) is defined simply by the difference between income (R = revenue) obtained and costs (C = cots) incurred in running a business (Nicholson, 1998). While income (R) and costs (C) are functions of output. The greater the output, the greater both the income and the costs. Mathematically, the maximization of company profits can be formulated as follows:

$$\pi(Q) = R(Q) - C(Q) \qquad (1)$$

Using derivatives theory, to reach maximum π, then:

$$\frac{dR}{dQ} = \frac{dC}{dQ} = \;\Leftrightarrow\; Marginal\ Revenue = Marginal\ Cost \;\Leftrightarrow\; MR = MC \qquad (2)$$

So, for maximum profit, the company will operate at the level of Output (Q) which makes MR = MC so that profit is very determined at a certain level of output. Meanwhile, in economic theory (Nicholson, 1998), it is formulated that Output (Q) is largely determined by the level of technology use (A), the amount of capital (K), and the use of labor (L). Thus, indirectly, profits are determined by the level of technology, capital, and labor used in business units. Mathematically Profit = f (A, K, L).

In line with the economic theory, the profitability of rural non-farm enterprises is also determined by the level of technology, capital, and labor in these businesses. In this context, the use of mobile phones and the internet can be seen as the use of technology in the production process to produce output that makes profit maximum. So theoretically, non-farm enterprises' profits are influenced by the use of mobile telephones and the internet (as a technological variable), as well as the level of capital and labor used in these business units. Mathematically written as:

Profit = f (mobile phone use, internet use, capital, and labor) (3)

3.3. Empirical Model

In general, rural non-farm business are managed on a household scale. Decisions on the allocation of capital, labor use, and other business decisions are strongly influenced by the socioeconomic characteristics of a household, the characteristics of the head of the household, and the characteristics of the business, as well as the characteristics of the area in which the business is run. Because capital data for the non-farm business units is not available, the empirical model used in this study is formulated as follows:

Profit = f (use of mobile phone, use of internet, charateristics of heads of households, characteristic of business, characteristics of business area) (4)

We can model equation (4) with a linear regression model and then predict it with the Ordinary Least Square (OLS) model, where the estimated coefficient of tmobile phone use and internet use shows the impact of mobile phones and the internet on profits. However, this approach has the potential to produce biased and inconsistent estimates due to the fact that the decision to use mobile phones and the internet is endogenous because these variables are influenced by profit levels and other factors. Regression models with endogenity will produce a biased and inconsistent when estimated using OLS (Gujarati & Porter, 2009). Therefore, it is necessary to find alternative empirical models and appropriate estimation methods to obtain unbiased and consistent analysis of the impact of mobile phone and internet usage.

One of the empirical frameworks for analyzing equation (1) by avoiding the weaknesses of the above model is the Propensity Score Matching (PSM) method. The advantage of PSM over the regression approach mentioned above is that it does not depend on functional assumptions about the relationship between profit (the dependent variable) and the independent variable (Becerril & Abdulai, 2010; Issahaku, et.all, 2018). Furthermore, PSM has the capacity to account for selectivity bias (Dehejia & Wahba, 2005). Matching method is a non-parametric approach that is used to measure the results of comparisons between groups that receive intervention (treatment) and groups that do not receive intervention (control). In PSM, the *control* group has the same characteristics as the *treatment* group called *counterfactual*. In this study, the *treatment* group is a rural non-farm enterprises group that uses mobile phones and/or use the internet.

The PSM model used in this study refers to that of basic model developed by Celiendo and Kopeinig (2008) with an equation model as follows:

$$\pi_i = D_i\pi_{1i} + (1 - D_i)\,\pi_{0i} \tag{5}$$

where D_i {0,1} is business unit using mobile phone and/or internet. $Di = 1$ if household *i* uses mobile phone or internet in its rural non-farm enterprise, and $Di = 0$ if household *i* does not use cell phone and/or internet. π_1 shows t household *i*'s profit performance of non-farm enterprise, when using a cell phone or the internet in its non-farm enterprise. Thus, the effect of the intervention on the household can be written as:

$$\tau = \pi_{1i} - \pi_{0i} \tag{6}$$

The potential *outcomes* of π_{1i} and π_{0i} cannot be simultaneously measured so only either one of them can be observed. Therefore, it is estimated that the average effect of an intervention's impact is the average treatment on the treated (ATT) value. This value can estimate the average impact of households receiving treatment (households using cell phones or the internet). The ATT value can be formulated as follows:

$$\tau\text{ATT} = \text{E}[\pi_{1i} - \pi_{0i}|D_i = 1] \tag{7}$$

$$\tau\text{ATT} = \text{E}(\boldsymbol{\tau}|D_i = 1) = E[\pi_{1i}|D_i = 1] - E[\pi_{0i}|D_i = 1] \tag{8}$$

ATT can also be calculated using this formula:

$$\tau\text{ATT} = E[\pi_{1i}|D_i = 1] - E[\pi_{0i}|D_i = 0] \tag{9}$$

In addition, in estimating the participation model to measure the propensity score matching, the *binary logit* model is used with the dependent variable being the household's decision to use mobile phones or the internet in rural non-farm enterprise (1 = having a cell phone or internet, and 0 = no). The formula is

$$\text{T}_i = Z_i\gamma + \varepsilon_i \tag{10}$$

where T_i, is *interest* variabel (mobile phone and/or internet use) and Z_i is control variable (characteristics of household, characteristics of business, characteristics business area), and ε_i is other variables that is not observed in observations.

4. Research Results and Discussions

This chapter discusses the results of the analysis. The data used is a cross section data taken from the Indonesia Family Life Survey (IFLS5) data in 2014 related to business activities in the non-agricultural and agricultural sectors, household demographic characteristics, and infrastructure characteristics in a certain area. Before arriving at the analysis using the PSM method, a descriptive analysis of the data used in this study will first be presented. The descriptive analysis will discuss two perspectives, namely the perspective of the level of adoption of mobile telephones and the internet, and the perspective of the level of performance of rural non-farm enterprises.

4.1. Descriptive Analysis of the Adoption of Mobile Phones and the Internet

Descriptive statistics results in Table 2 show that the number households using mobile phones in non-farm enterprises (NFE) reaches 46.41% of the total sample, while the number of household using the internet is significantly lower at only 56 households or 3.94% of the total the sample. The earlier development of mobile technology in Indonesia and its features that are easier to operate, makes mobile phone penetration relatively high when compared to internet technology. The most percentage of age group that adopts mobile phones in their business is the 31-40 years age group, with almost equal percentage as the 19-30 years age group. Similar finding is shown in the percentage of internet use in business. This shows that the younger the age of the heads of households, the more likely mobile phones and the internet are used in non-farm enterprises. The younger age group tends to have higher cognitive abilities and creativity, whereas the older age group tends to be conservative about new technology. In terms of innovation and knowledge, the younger age groups are likely to have more updated compared to the older age groups, following the very fast and dynamics technological developments. With more updated information, younger age group have more opportunities to find out how to use and access to the technology.

Table 2. Percentage of Mobile phone and internet adoption based on Socio-demographical Characteristics of Heads of Households

Variable	Mobile Phone (%)			Internet (%)		
	Adopter	Non-Adopter	Total	Adopter	Non-Adopter	Total
Age Group						
19-30	51.09	48.91	100	5.11	94.89	100
31-40	57.64	42.36	100	5.09	94.91	100
41-50	49.31	50.69	100	3.58	96.42	100
51-60	40.25	59.75	100	2.48	97.52	100
>60	29.20	70.80	100	3.98	96.02	100
Gender						
Male	48.54	51.46	100	4.06	95.94	100
Female	32.63	67.37	100	3.16	96.84	100
Main Job						
Formal	57.33	42.67	100	9.33	90.67	100
Informal	43.49	56.51	100	2.50	97.50	100
Years of Schooling						
<7	35.71	64.29	100	1.60	98.40	100
7-9	54.94	45.06	100	3.00	97.00	100
10-12	62.50	37.50	100	7.43	92.57	100
>12	70.37	29.63	100	17.28	82.72	100
Total per Variabel	46.31	53.69	100	3.97	96.03	100

Source: (IFLS 2014, processed)

Meanwhile, with analysis on gender of the heads of the households, it shows that the male group has a higher percentage of penetration of mobile phone and internet adoption compared to the female group. Men and women differ significantly in terms of attitudes towards risk, women's risk-averse behavior tends to result in lower levels of technology adoption (Byrnes, Miller, Schafer, 1999). Men and women also differ in their attitude to technology. Girls are more ambivalent about technology than boys and are less likely to repair technology when damaged (Dholakia, Dholakia, & Kshetri, 2004). Furthermore, judging from the years of schooling of the heads of the households, the percentage of mobile phones and internet adopters in non-farm enterprises is indicated by above 12 years of schooling group, higher when compared to non-adopters with an average of 6 years of schooling. These results are as expected, that those with higher education tend to have the knowledge needed in the operation of mobile phones and the internet. The adoption of information and communication technology based on these three variables is in line with research conducted by Leung and Wei (1998) that those who are younger and better educated influence one's behavior in adopting a technology. In addition, judging by the main occupational sector of the heads of the households, those who work in the formal sector have higher rates of mobile phones and internet adoption in non-farm enterprises compared to those who work in the informal sector. Those who work in the formal sector, especially in large companies, tend to have opportunities to interact with modern information technology in their work. This gives an influence on someone to adopt telecommunications equipment.

Table 3 shows that households with farmland assets have a higher percentage of mobile phone adoption compared to households without a farmland assets. The same results are also shown in the percentage of internet adoption. Farmland ownership indicates households' ability to obtain or adopt mobile phones or internet. While based on the number of workers, non-farm enterprises with more than 6 employees have a higher percentage of mobile phone and internet adoption compared to those which only employ 6 or less workers. With greater labor input, the needs for coordination increases. This encourages companies to adopt information technology such as mobile phones and the internet that can reduce coordination cost. Dholakia, Johnson, Della, & Dholakia (1993) suggest that business size, as measured by the number of employees, is particularly important for the benefits of e-mail and communications by mobile phones. The service sector also has a higher percentage of mobile phone and internet applications in business compared to non-services. Dholakia, et.all (1991) also observed that business sector differences play a role in the acquisition of telecommunications products and services. His findings show that information technology has a more important role in the service-oriented sector than in the manufacturing or trade sectors. In a relative sense, the service sector is more likely to be oriented toward business partners compared to the manufacturing or trade sectors which depend mainly on equipment.

Judging from households' connectivity to electricity in Table 3, it is seen that households that are connected to electricity have a higher percentage of mobile phone and internet adoption compared to households which are not connected to electricity. This shows that the availability of energy sources for the operation of technology can increase the likelihood of households to adopt technology. In addition, Table 3 also shows that the more availability of BTS infrastructure with a higher density in an area means that the tendency of households in the region to adopt mobile phones and the internet also increases. The availability of BTS reflects the quality of signal received by the households. With better quality, the possibility of information technology penetration is also higher.

4.2. Descriptive Analysis of Rural Non-Farm Enterprises Performance

It can be seen from Table 4 that rural non-farm household enterprises that adopt mobile phones or internet have a higher average net business income than enterprises that do not adopt mobile phones or internet. Hengst and Sol (2001) suggest that mobile phones and the internet are telecommunications devices that are able to facilitate access to information so as to reduce the cost of coordination. This will ultimately improve the companies' performance. In addition, these telecommunications devices are also able to reach a wider market thereby encouraging business expansion (Donner, 2006).

Donner (2006) and Gibson and Olivia (2010) find that good infrastructure will drive business performance. Therefore, regions with good infrastructure such as Java Island should offer wider opportunities for businesses to deliver greater performance. However, Table 4 shows that businesses operating in Java have a smaller average of non-farm enterprises net income compared to those outside of Java. This might be caused by tough business competition, especially from urban businesses in Java which makes rural non-farm businesses difficult to develop. In addition, it is also driven by relatively simple technological advatecement and the average low human resource ability. Based on landfarm ownership, the average net income of non-farm enterprises is almost equal to that of households without landfarm ownership.

Table 3. Percentage of Mobile phones and internet adoption based on socio-demographical characteristics of household business and infrastucture

Variabel	Mobile phones (%)			Internet (%)		
	Adopter	Non-Adopter	Total	Adopter	Non-Adopter	Total
Land Ownership						
Owner	50.92	49.08	100	4.88	95.12	100
Not Owner	41.27	58.73	100	2.86	97.14	100
Number of NFE worker						
<3	42.58	57.42	100	2.07	97.93	100
3-6	48.11	51.89	100	4.94	95.06	100
>6	88.46	11.54	100	19.23	80.77	100
NFE Business Sector						
Services	57.83	42.17	100	7.35	92.65	100
Non-services	43.19	56.81	100	2.98	97.02	100
Electricity						
Connected	47.21	52.79	100	4.00	96.00	100
Not connected	35.42	64.58	100	3.13	96.87	100
Number of BTS per 1 million population						
<501	41.99	58.01	100	3.45	96.55	100
501-1000	47.03	52.97	100	3.76	96.24	100
>1000	62.50	37.50	100	7.69	92.31	100
Total per Variabbel	46.31	53.69	100	3.97	96.03	100

Source: (IFLS 2014, processed)

In terms of non-farm enterprises business sector, the largest average net income is shown by the service sector which is the sector with the highest adoption of telecommunications equipment. In addition, the service sector also prioritizes skill capital compared to physical capital so that this sector tends to meet low costs and encourage higher income compared to the other two sectors. Judging by the length of business, the lowest average net income of non-farm enterprises is shown by businesses that stand in the range of 0-4 years. This result is possible because those who have been operating than 5 years usually have not reached the BEP (Break Even Point) so that the income received are relatively still low. Meanwhile, those which have been operating for 5 years or more in non-farm enterprises have averagely higher income than those who have only been operating for less than 5 years. More experienced enterprises have the tendency of having more permanent consumer networks.

Based on the theory of human capital, an investment in improving the quality of human resources will encourage an increase in the quality and performance of individual work. One way to accumulate knowledge and skills is to attend formal education. In Table 4 it is presented that the higher a person's years of schooling, the higher the average net business income. The average income of non-farm enterprises has increased along with the increase in education levels pursued. On the contrary, the business location sector with on Java Island shows that those on Java island show lower net income compared to those outside Java. It is possible that his is caused by the tight competition on Java with a considerable number of urban areas. This puts the relatively small-scale rural non-farm enterprises under pressure on a competition with urban products which limit their market expansion.

4.3. Logit Model Estimation Results

The PSM method is adopted for making score matching between groups of mobile phone users and non mobile-phone users (which is counterfactual for cell phone user groups). Likewise, the PSM method is applied for analyzing the impact of internet use on the performance of non-farm enterprises, by making score matching between groups of internet users and their counterfactuals. To obtain a score matching, this study uses a logit model to calculate score matching and at the same time analyzes which factors significantly influence the use of mobile phones and the internet at the level of households which own non-farm enterprises. The results of the logit model for determining mobile phone or internet adoption in business are presented in Table 5. Of the 14 estimated variables, 10 have significant influence on mobile phone adoption and only 6 have significant influence on internet adoption in non-farm enterprises. Cailendo and Kopeinig (2008) suggest that the inclusion of insignificant variables in the tendency score specifications will not bias the estimated propensity score or make them inconsistent, yet increases their variance.

Table 4. Average Net Income of Rural Non-Farm Enterprises based on Housejold Characteristics

Variable	Mean (million rupiah per month)	Observation total	St.Dev
Mobile phone			
Adopter	21.68	660	47.04
Non-Adopter	9.18	762	18.63
Internet			
Adopter	32.68	56	71.26
Non-Adopter	14.25	1366	32.93
Landfarm ownership			
Yes	16.23	758	36.99
No	13.55	664	33.38
NFE Sector			
Service	16.83	313	51.65
Non Service	14.46	1109	29.18
NFE age			
0 - 4 years	11.08	549	27.23
5 - 10 years	17.99	374	47.63
11 - 15 years	20.06	161	35.55
>15 years	15.56	338	30.16
On Java Island			
Yes	9.54	755	19.77
No	21.14	667	46.42
Years of Schooling			
<7	11.49	812	24.09
7-9	15.91	233	34.18
10-12	22.05	296	55.88
>12	21.47	81	32.78
Total Observasi	1422		

Source: (IFLS 2014, processed)

Based on the estimated logit, older age reduces the likelihood of mobile phone use in business, while an additional year of schooling increases the likelihood of mobile phone and internet usage. This fulfills the expectation that those who are educated have the knowledge needed to operate mobile phones and the internet, and the older age tends to be conservative towards things that are considered new. These results are consistent with the findings of Leung and Wei (1998) who stated that in general adopters of new technologies tend to be younger and more educated. In addition, households with large non-farm enterprises, in the number of workers, and those engaged in the service sector, tend to be more likely to use mobile phones and the internet. The large number of workers demands high communication needs, similarl with the service-oriented service sector. Similar result was also shown by households with farmland ownership. This shows the important role of household assets or wealth in the use of mobile phones. On the contrary, the length of the business actually reduces the possibility of adopting mobile phones and the internet in the business. This is possible because the longer the business operates, thebhigher the tendency for them to have large loyal customers so that the demand to expand the market tends to be low.

Table 5. Logit model estimation results

Independent Variables	Phone		Internet	
	Koef	SE	Koef	SE
Age	-0.01***	0.00	0.01	0.01
Gender	0.30*	0.18	-0.32	0.48
Education	0.09***	0.01	0.17***	0.03
Main Job (Formal)	0.34**	0.14	0.94***	0.31
Owner	0.94**	0.46	0.05	0.94
Worker	0.22***	0.04	0.29***	0.05
NFE_Jasa	0.68***	0.14	1.09***	0.30
NFE_year	-0.01**	0.00	-0.04**	0.01
Landfarm	0.34***	0.11	0.58*	0.31
Electricity	0.32	0.24	-0.02	0.63
Blackout	-0.05	0.14	0.03	0.41
Speed	0.00	0.00	0.00	0.01
Signal	0.00	0.00	0.00	0.00
Java	-0.37**	0.15	0.56	0.41
Cons.	-2.01***	0.63	-7.34***	1.50

* signifikan in level 10 %, ** signifikan di level 5 %, *** signifikan di level 1 %

Number of Obs 1.422 household

Source:(IFLS 2014, processed)

The estimated logit coefficient will be used for propensity score matching estimation as a basis for estimating the treatment effect. This propensity score mathing is used to balance the estimated distribution of explanatory variables between the treatment and counterfactual groups. Determination of Matching Algorithm will compare 4 methods, namely Nearest Neighbor (NN) with replacement, Nearest Neighbor (NN) without replacement, Radius Caliper, and Kernel Matching. Determination of the method to be used depends on the results of the distribution of propensity score matching and the area of common support that can be seen in Appendix 1. In this section we will see the distribution of propensity scores between before and after matching.

According to Caliendo and Kopeinig (2008), if the distribution of scores in the treatment and control groups is different, the nearest neighbor (NN) with replacement method is more appropriate to use. Conversely, if the distribution value is proportional, then the use of oversampling estimation or kernel matching is more suitable to get a higher estimation accuracy. From the results of the distribution of propensity score matching and the common support area in Appendix 1, it can be seen that a distribution that has a comparable value is the mobile phone use treatment in the NFE. Meanwhile, the treatment of internet usage in the NFE has a different distribution. Therefore, kernel matching will be used for mobile phone adoption treatment, NN with replacement is used for the internet use.

Table 6 shows the covariate balancing indicators before and after matching, as well as a sensitivity analysis that assesses the quality of matching and shows how strong the estimation is. The results show that before matching, the Pseudo R-square value and Chi-square (LR Chi2) likelihood ratio of the four methods resulted in a decrease (lower) value after matching, both on mobile phone and internet treatments. These results indicate that matching significantly reduces the bias between the characteristics of cellphone or internet usage with non-users, and is able to balance the characteristics of the two groups. Furthermore, the average bias before matching was 22.40% and 28.80% (for mobile phone and internet treatment), whereas after matching the reduction bias was reduced to 3.20% in mobile phone treatment (Kernel Matching) and 14.80% in internet treatment (NN with replacement). This shows a reduction in the percentage of 85.71%

and 48.61%, respectively. According to Rosenbaum and Rubin (1983), a reduction in bias of above 20% is large enough to indicate that an estimate is reliable.

4.4. Results Strength Testing

Table 6. Matching Quality Test Results

Matching Estimator	Before Matching	After Matching			
		NN with replacement	NN without replacement	Radius Caliper	Kernel
Phone					
Pseudo R2	0,111	0,006	0,066	0,004	0,004
LR chi2	218,84	11,82	119,32	7,71	8,01
p>chi2	0,000	0,621	0,000	0,904	0,889
Mean Bias	22,40	4,00	14,80	3,20	3,20
% Bias Reduction		82,14	33,93	85,71	85,71
Prob > F		0,841	0,000	0,879	0,859
Critical level of Gamma		1,5 - 1,8	1,5 - 1,8	1 - 1,2	1,1 - 1,3
Internet					
Pseudo R2	0,207	0,058	0,030	0,046	0,059
LR chi2	97,55	9,07	4,59	7,15	9,13
p>chi2	0,000	0,827	0,991	0,929	0,822
Mean Bias	28,80	14,80	10,60	12,20	13,80
% Bias Reduction		48,61	63,19	57,64	52,08
Prob > F		0,911	0,994	0,000	0,000
Critical level of Gamma		1,0 - 1,6	1,0 - 1,8	2,0 - 3,0	2,0 - 3,0

Source: (IFLS 2014, processed)

Furthermore, a sensitivity analysis is carried out to find out how strongly variables outside of observation can influence the selection process carried out to obtain the implications of matching analysis. This analysis uses Wilcoxon's signed-rank test in which the results are free from hidden bias when the gamma value is significant at the 5% level (α=0.05). The sensitivity analysis for hidden bias in Table 6 shows the critical level in the treatment of mobile phones and the internet is significant at the level of $\alpha = 0.05$ at gamma = 1.1 - 1.3 and 1.0 - 1.6. These results indicate that the model is free from hidden bias, but is very responsive to factors that are not observed.

4.5. Discussion on the Impact of Mobile Phone and Internet Use on Rural Non-farm Enterprises' Performance

After obtaining a matching score through the logit model, the next step is to match the mobile phone/internet user groups and the control group to obtain a *counterfactual*. There are four matching methods considered, namely Nearest Neighbor (NN) with and without replacement, Radius Caliper, and Kernel Matching. With these four matching methods, a t-test is then performed to test whether the average performance (profit) of non-farm enterprises using mobile phones or internet is higher than the counterfactual group's performance (profit). In general, all four methods show that the use of mobile telephones or internet in rural non-farm enterprises gives a significant positive correlation to non-farm business profits. These results are presented in Table 7. Referring to the results of the score distribution in Appendix 1, the interpretation of the ATT value in the mobile phone treatment will refer to the Kernel Matching method, while the internet treatment will refer to the NN with replacement method.

Based on the Kernel Matching estimation results in Table 7, it is found that the use of mobile phones in business gave a significant correlation (level $\alpha = 0.01$) in increasing the profit of rural non-farm household enterprises by 9.42 million/year. The impact of mobile phone use in increasing the profitability of rural non-farm household enterprises is in line with the literature which states that mobile phone plays a role as a platform to find sources of information about input markets such as more affordable and higher quality raw materials (Arifin, 2012: Ogutu, et.all, 2014) so that it is set as a production factor that can improve rural business performance. In addition, with the use of mobile phones, business operators can reach potential consumers (Frempong, 2009; Donner, 2006) not only in the area around the business location, but also those outside the village area. Voice communication is very important for rural areas, especially in developing countries. Lack of transportation infrastructure, low levels of education, and migrant-labor-intensive workforce are some of the characteristics of rural areas that emphasize the need for real-time voice communication.

Table 7. The Effects of Mobile Phone and Internet Use on Rural Non-Farm Enterprises Performance

Outcome Indicator	Treatment	Methods of Matching	ATT	SE	T-stat	Treated		Control	
						On Support	Off Support	On Support	Off Support
Profit NFE	Phone	NN with replacement	10.54***	2.32	4.54	657	3	762	0
		NN without replacement	11.84***	1.99	5.95	657	3	762	0
		Radius Caliper (0.1)	9.27***	2.01	4.59	660	0	762	0
		Kernel	9.42***	2.02	4.66	657	3	762	0
	Internet	NN with replacement	18.17*	10.56	1.72	56	0	1366	0
		NN without replacement	16.82*	10.28	1.64	56	0	1366	0
		Radius Caliper (0.1)	13.61	9.64	1.41	56	0	1366	0
		Kernel	14.37	9.62	1.49	56	0	1366	0

* significant in level 10 %, ** significant in level 5 %, *** significant in level 1 %
Number of Obs 1.422 household
Source: (IFLS 2014, processed)

Furthermore, based on the estimation results of the Nearest Neighbor (NN) method with replacement in Table 7, it can be seen that the use of the internet in rural non-farm enterprises provides a significant correlation (level $\alpha = 0.1$) with 18.17 million/year of increased non-farm enterprises productivity. This means non-farm enterprises households that use the internet have a higher average net income of 18.17 million/year compared to non-farm enterprises households that do not use the internet (see table 7). Similar results are also obtained by other matching methods. Robustness check results show the consistency of the results. In other words, the results of this study provide enough evidence related to the effect of internet use in increasing non-farm enterprises productivity. This result is in accordance with the empirical literature which found an important role of the internet in reducing transaction and coordination costs (Litan & Rivlin, 2001) so as to improve household welfare in rural areas (Ariyansyah, 2018).

5. Conclusion

5.1 Conclusion

This study examines the impact of mobile phone and internet usage on the performance of rural non-farming enterprises. As an evaluative study, PSM (psmatch2) and t-effect version are used as tools for estimating the impact. Highlights from the results show that the use of mobile phones by rural non-farm enterprises has a significant positive effect on business profits (non-fam enterprises performance), as well as the use of the internet in business.

This study also found that the use of internet was able to increase profits by Rp18.17 million/year. While the use of mobile phones, is able to increase profit by Rp9.42 million year. So, it can be concluded that the use of the internet has a greater influence on business performance compared to mobile phones. This result is driven by the fact that the internet is not only be able to be used for communications, but also to find information through websites, as well as to promote products in visual forms. Meanwhile, mobile phone only highlights its features for communication, especially real time communication. The role of mobile phone and the internet in facilitating access to information for both input and output markets will improve the quality of information received so that it can support economic agents to make informed decisions. In addition, this technology is able to create shorter information transmission process that saves time and costs, which eventually encourage business performance improvement.

5.2 Policy Recommendation

A clear understanding of the characteristics of rural non-far enterprise and business actors in terms of their education, size, and business operating sectors is an important consideration prior to dissemination of technology that targets to improve their performance. Its impact, which is driving the economic growth, making these findings highlight the necessity of expanding the scope of mobile phone and internet penetration in rural areas. Some policies can help increase the penetration of the technology in rural areas.

The average low level of education in rural areas resulted in less optimal use of ICT. Basic education curriculum, which on average can be accessed by rural households, should include basic knowledge of the importance of telecommunications technology. Digital literacy also contributes to the development of such lagging regions. In addition, the rural non-farm enterprises sector needs to be strengthened with the support of the application of digital technology in its business activities, especially in terms of marketing. With digital technology, marketing can be done online which can eventually encourage market expansion in this sector.

In addition, the affordability of the services that can be accessed by rural households will also encourage rural households to embrace the communication technology, considering that most of internet users come from the high-income households, whereas the average rural household income is lower than urban households. Finally, the penetration of telecommunications technology in rural households will accelerate the process of structural transformation, with an increase in the non-farm enterprises sector, especially in remote areas. It is expected that such transformation can encourage household income increase and accelerate economic growth in the region.

5.3 Reccomendation

This research is limited to IFLS survey data which only covers 19 provinces so it does not reflect the overall condition of Indonesia. For this reason, It is necessary for further research to include a larger research sample, which includes household data in all regions of Indonesia. Using data with a longer time period will also provide more comprehensive results.

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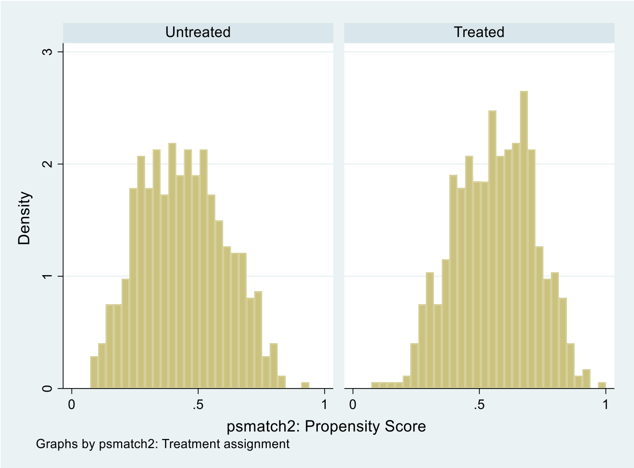
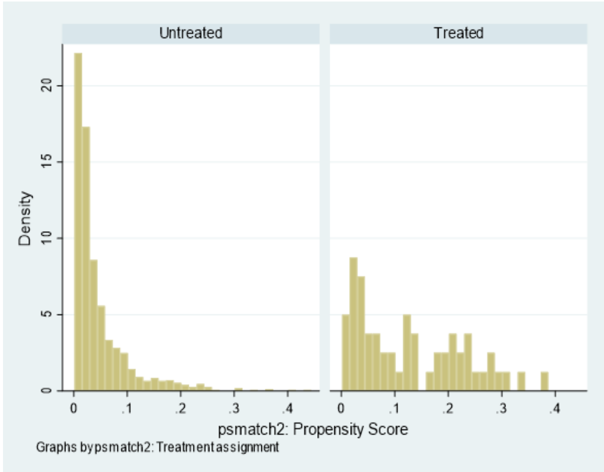
Appendix 1

Comparation of *Propensity Score* distribution

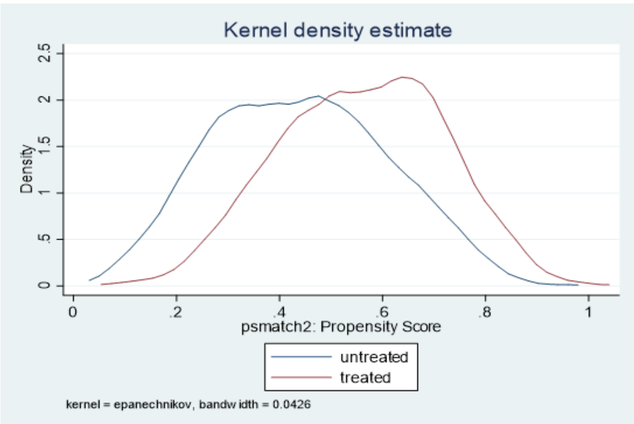


Treatment: Phone

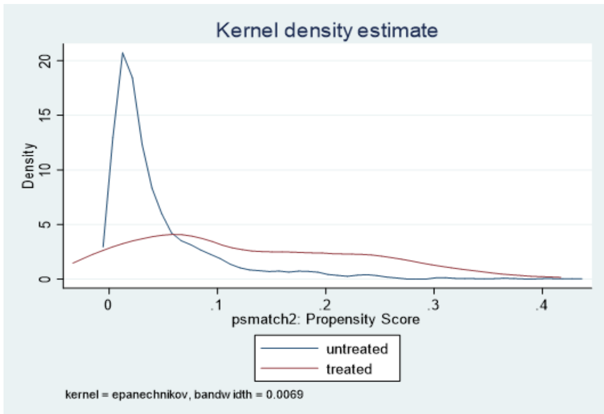


Treatment: Internet

Results of *Common Support*



Treatment: Phone



Treatment: Internet

Source: IFLS 2014, processed

Figure 2. Comparation of Results of Propensity Score and Common Support* Distributions