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Article

Household Economic Welfare During the Rise of Mobile Phone Expansion in Indonesia

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Abstract

The proliferation of mobile phones in developing countries has significant implications for those countries. Although numerous studies have examined the various advantages of mobile phone use, the relationship between mobile phone access and the economic welfare of households has received comparatively little attention. This paper examines the effects of mobile phone on household expenditures in 2007 and 2014 utilising the Indonesian Family Life Survey (IFLS) combined with Potential Village Survey (PODES). Ordinary Least Square (OLS), Endogenous Treatment Regression (ETR), quantile regression, and two-way fixed effect estimations are used to identify the homogeneous and heterogeneous effects of mobile phone use. According to the estimated results, mobile phone access and signal quality significantly increases household expenditure. According to the results of quantile regression, mobile phone access has the greatest effect on the upper expenditure distributions. It is highlighting the importance of promoting a policy that increases mobile phone and the supporting infrastructure on the lower expenditure distributions.

Keywords: mobile phones; household; economic welfare; Indonesia.

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1. Introduction

Mobile phones represent one of many Information Communication and Technology (ICT) equipment that has become a global phenomenon and has spread rapidly worldwide. Furthermore, internet access, which is now standard in mobile phones, has already been identified as a global target. Based on National Socioeconomic Survey Data (Susenas), the proportion of internet users in Indonesia increased from 32% in 2017 to 44% in 2019. Even though it is proliferating, the number of internet users in Indonesia is still low; even according to Susenas data for 2019, it is still below the Millennium Development Goals (MDGs) target by 50% of the population. This achievement is considered to be slowing down because the MDGs have now been replaced by Sustainable Development Goals (SDGs), whose indicators will continue to rise along the year (International Telecommunication Union, 2013). This condition could be attributed to the diverse archipelagic territory of Indonesia. Therefore, extending mobile phone and internet usage conditions in Indonesia is complex and challenging.

Indeed, both mobile phones are expected to be a solution to accelerate the flow of information. Stiglitz (1985) noted that information could reduce market failures caused by asymmetric information between economic agents. Information has become an economic value because it can facilitate economic agents to make better economic decisions than in conditions without information. However, this information's availability may be expensive because it is sometimes challenging to access. Certain areas, for example, agricultural and rural areas in the outermost regions of Indonesia, require satellite and microwave link technology with a much more expensive cost, and the phone itself has different features than the regular phone (Bachtiar et al., 2020).

The Indonesian government has established several strategic policies to encourage the usage of mobile phones or mobile internet for all Indonesian citizens, especially in the frontier, outermost, and underdeveloped areas (well-known as terdepan, terluar, tertinggal 3T in Indonesia), such as rural areas on the small outer islands around Indonesia. Through Presidential Regulation (Perpres) No. 96 of 2014 concerning the 2014-2019 Indonesia Broadband Plan, the government is trying to show its commitment to reducing the cost of accessing this information. It is critical to determine whether mobile phone provision provides welfare benefits not only to the business sector but also to every household or individual. Furthermore, it is also essential to know which individual characteristics benefit most from mobile phones and which do not.

1.1. Research Problem

While several researchers (Aker & Mbiti, 2010; Hartje & Hübler, 2017; Muto & Yamano, 2009; Zanello, 2012) argue that ICT in general have contributed to individual household economic welfare, several other studies (de Silva & Zainudeen, 2007; Tadesse & Bahiigwa, 2015) argue that ICT alone cannot be a silver bullet or a significant factor in improving household economic welfare. Differences in household characteristics also come with different welfare results regarding adopting ICT. Then, ICT continuously develops over time. For example, the emerging mobile internet network services might begin from the GSM era in the 1990s until now the 4G become the golden standard for Indonesia's internet network. Furthermore, the introduction of mobile phone operating system upgrades undoubtedly had a different impact on the flow of information and its economic benefit. With this new perspective and ICT update, there is an urgent need to comprehend and evaluate the impact of ICT on household welfare.

As far as the author is aware, it is not easy to look for studies concentrating on the relationship between ICT and economic welfare at the household level in Indonesia. In contrast, we can easily search for studies that examine this relationship at the macro level with various variables and data availability over time. For example, Ariansyah (2018) used data from ASEAN countries, including Indonesia, from 2005 to 2016, and Farhadi et al. (2012) used data from Indonesia and 158 other countries from 2000 to 2009. Then, most recently, in 2020, Patria & Erumban (2020) used the average aggregate data for Indonesian provinces in the 2012-2016 period.

Some studies try to explain the relationship between ICT and performance at the Indonesian household level in specific scope and certain parts of Indonesia (see Esquivias et al., 2020; Rahayu & Riyanto, 2020). Some potential problems that might arise from the study of Esquivias and Rahayu & Riyanto can be explained as follows. First, Esquivias' research wants to see the relationship between digital technology and household income with only Eastern Indonesia's scope. Meanwhile, Rahayu Riyanto attempts to explain the role of mobile phones in non-agricultural household income. Both previous studies attempted to explain using only cross-section data. The consequences of the findings obtained from these studies are that it is difficult to generalize or there is a potential external validity issue because different regions (for example, east and west area, farm and non-farm or urban versus rural) have different socio-economic characteristics and information infrastructure. Therefore, a study examining the effects of ICT on household welfare using broader data and household characteristics in Indonesia is still attractive.

Second, Esquivias and Rahayu Riyanto's research examines the effect of ICT on household income. Meanwhile, the effect of ICT studies on household expenditure is unexplained. The household expenditure may more accurately reflect the actual level of household welfare, given that many people can fund their needs immediately using financial instruments. Amartya (Sen, 1988) revealed that per capita income might not represent society's standard of living. Therefore, the informal transactions could not be identified. Consumption or expenditures addresses immediate needs such as food, housing, schooling, and healthcare, making it a critical indicator of short-term welfare and compensating for the deficiencies associated with unreported income (Meyer & Sullivan, 2003).

Third, ICT usage may affect households at the top and bottom of households income and expenditures distribution, as ICT adoption can affect resources and capital that differ between poor and wealthy households. De Silva and Zainudeen (2007) discovered that in their study, more than 80% of poor household respondents used mobile phones only to communicate with family or friends, while less than 15% used them for business. As a result, household heterogeneity is important; households with different ICT adoption characteristics pursue different goals. Estimating ICT treatment and its variation along the welfare distribution would be interesting.

1.2. Research Objective and Brief Section

This study investigates the impact of mobile telecommunication access on household welfare and its distribution in Indonesia. Section 2 describes the theoretical framework explaining how mobile phones can influence a household or individual welfare and review relevant literature about it. Later, section 3 presents data and empirical methods in this study. Then section 4 provides the empirical results, while section 5 discusses and concludes the whole paper.

2. Theoretical Framework

2.1 Human Capital Theory

According to Becker (1975), assuming all other variables remain constant or equal, a person's income would vary due to the difference in the amount invested in human resources. For example, suppose that a worker with mobile phone internet proficiency performs better at work and is more likely to be effective than someone without mobile phone Internet proficiency. As a result, anyone with that experience will strive for a higher salary. The sacrifice made by these individuals investing in human resources is shown by their ability to use this ICT device efficiently.

Welfens (2008) illustrates how ICT influences efficiency in his research; ICT is seen as a catalyst for creativity in a service or product and can potentially promote knowledge dissemination. Welfens also gives an agricultural example: farmers using another ICT device, the mobile internet, to gather information about what crops to grow in the upcoming planting season, which is expected to increase their income. Additionally, the internet may provide information about how to grow healthy plants and control pests. This kind of information might increase the quality of work and decrease the time required to complete the work. These factors would contribute to their income and wage growth.

2.2 Transaction Cost

Transaction Cost Economics is the principle that commercial transactions may not be costless (TCE). According to Hobbs's (1997) viewpoint, transaction costs can be classified into three categories: information, negotiation, and monitoring costs. Charges for information may be charged before the completion of a transaction. It also includes the costs associated with collecting information about product and service prices and the costs associated with selecting the proper trading partner. Before the mobile internet age, information sharing occurred primarily through face-to-face contact, augmented by postal services, telegraph, telephone, and sometimes even fax.

However, as time progresses, the acknowledgement of developments on the mobile internet has changed how information is gathered and exchanged, making it more accessible and affordable than ever. Logically, as the cost of information decreases, transaction costs decrease as well. For instance, in households, if someone can access information about fair market prices for a specific product or service through the mobile internet, they can easily trade to optimize their utility.

Greenberg (2005) argues that using ICT effectively will assist households in gathering commodity price information relevant to household production. This ICT can help mitigate middleman influence and maximize household income. Additionally, using ICT may provide an opportunity to increase sales in a manner that is frequently linked to a potential seller online, either through ads or promotional materials.

2.3 Literature Review

The potential economic gains from investing in ICT have been the subject of previous research from a variety of countries. There is a positive correlation between the use of ICT and farmers' household participation in markets and transactions, as well as the price they receive for their goods. Muto & Yamano (2009) discovered that expanding mobile phone coverage in Uganda decreased marketing expenses, increasing consumer engagement among farmers and rising perishable crops, including bananas, in remote areas. Zanello (2012) discovered that obtaining consumer information from mobile phones increased rural households' market participation in Northern Ghana by lowering search costs. In summary, farmers gain from ICT because they are an essential instrument for obtaining consumer knowledge. Market information, in particular, will help farmers make more informed decisions on when and where to sell their goods, ensuring they earn a fair price for their products.

The literature on the impact of mobile ICT on household welfare can be clarified by the fact that ICT may promote access to job vacancies and enhance mutual contact between employees and families or social circles at home. Dammert et al. (2013) conducted research in Peru on the interaction between digital job market intermediaries and work benefit expectations (for example, salary offers). They discovered that sending job market information to jobseekers through Short Messaging Services (SMS) boosts job gain prospects and potentially increases job positions. Hartje & Hübler (2017) observed that mobile ICT, such as smartphones, facilitates local labour market inclusion and labour mobility (commuting), whereas it encourages workers' migration to work in the formal sector.

The beneficial effects of ICT on productivity, promotion, and household labour involvement mean that ICT usage can result in direct income gains. As Aker & Mbiti (2010) explain, this is because technological advancements make it easier to send and receive money, streamline administrative duties and household, connect people with one another, offer professional and medical advice, and even reduce the risk of financial loss.

However, according to De Silva and Zainudeen (2007), perceptions about the potential economic gains of ICT use appear to be mixed. For evidence, approximately a quarter of Sri Lanka's poorest residents indicated that having direct access to a mobile phone has harmed their capacity to gain or even invest. De Silva & Zainudeen also discovered that access to telecommunications is often not seen as growing people's earning and cost-cutting opportunities. Maybe the poorest in society could not explicitly use their phones for business purposes. They also discovered that over 80% of household respondents from Pakistan, India, Sri Lanka, the Philippines, and Thailand used mobile phones only to communicate with family or friends, but less than 15% used them for business. Tadesse & Bahiigwa (2015) observed that mobile phones did not play a significant role in determining farmers' marketing decisions or farm gate pricing, referring to a scarcity of knowledge resources capable of handling meaningful information among farmers.

The theoretical and literature review summary of mobile phones' influence on household welfare from the perspective of theoretical review is shown in Figure 1.

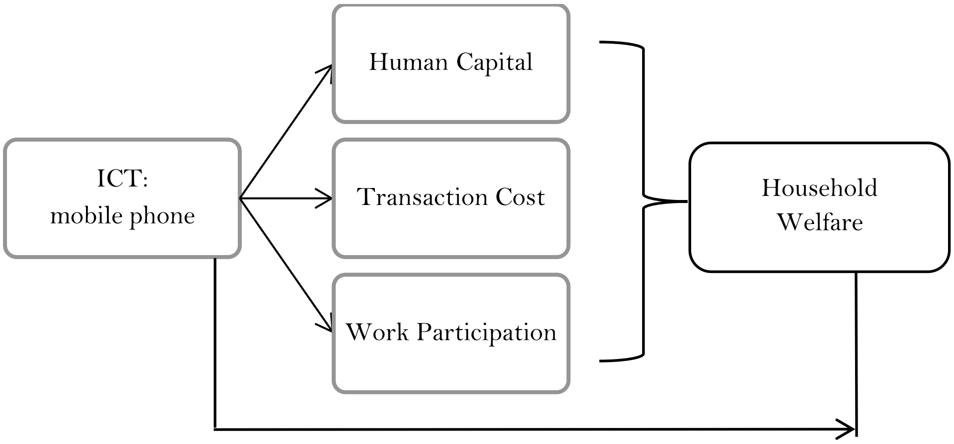


Figure 1. The Theoretical Framework of Mobile Phones Influence Household Welfare

Source: processed by author, 2022

Previous pieces of literature and theories have indicated that mobile ICT have a direct impact on human capital (Becker, 1975; Welfens, 2008), market transactions cost (Muto & Yamano, 2009); (Zanello, 2012), and also household decisions relating to work participation (Dammert et al., 2013; Hartje & Hübler, 2017) that, in turn, may affect household welfare indirectly. Human capital, transaction costs, and labour force participation all play a role in determining household income, which in turn can affect other facets of household life (as shown in Figure 1). It does this in a number of ways, including by strengthening social networks, offering technical and medical consultation services, and lowering the risks associated with using mobile ICT (Aker & Mbiti, 2010).

Based on the summary in Fig. 1 or previous studies in other parts of the world, we could assume that household income or output (Y_h), and information transaction costs (ITC), are affected by the use of ICT (mobile phone in this study, indexed byICT_i) and a vector of exogenous variables (X_i). Following the work by (Khanal & Mishra, 2016), an optimal solution for a household's utility maximization problem can be expressed as follows:

$$H_i = \{Y_h(ICT_i, X_i) - FTC - ITC(ICT_i, X_i)\} \quad (1)$$

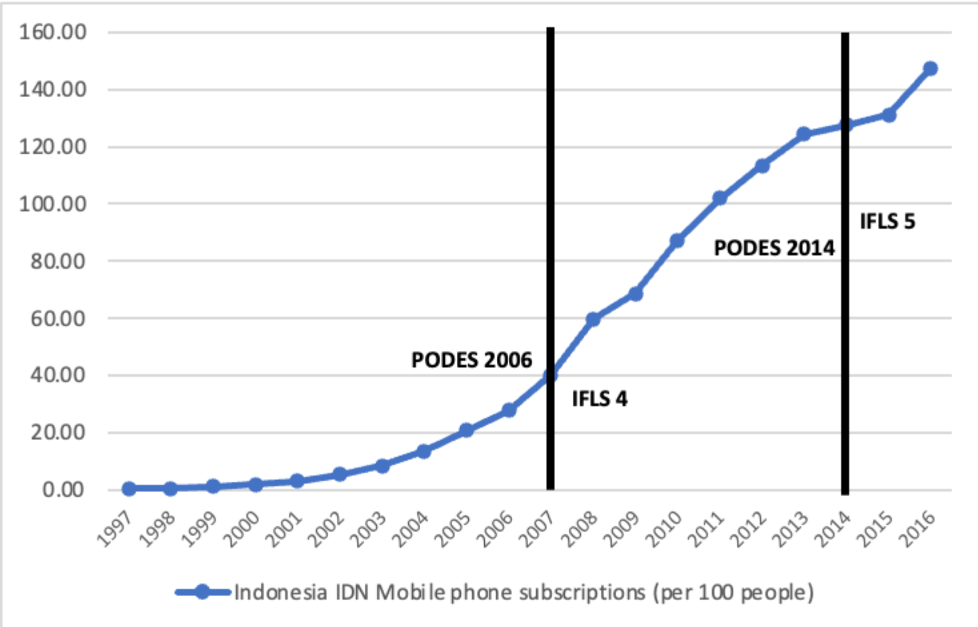
Where FTC refers to fixed transaction costs associated with products and services. Equation (1) shows that the use of ICT affects household income and output (Y_h), information transaction costs (ITC).

3. Empirical Method

3.1 Data

This study plans to use two secondary data sources from Indonesia, namely the Indonesian Family Life Survey (IFLS) collected by the RAND Corporation and the Village Potential Survey (PODES) from the Central Statistics Agency (Statistics Indonesia). IFLS is longitudinal data obtained from households in Indonesia. In this study, the authors focus on waves 4 (2007) and 5 (2014), the period when mobile phone technology developed. However, the ownership and use of the mobile phone are detailed only in the 5th (2014) wave of IFLS and not in the previous wave. So that in order to take advantage of both the cross-sectional and longitudinal properties of IFLS, the authors use PODES data information regarding mobile phone signal quality at the village level in 2006 and 2014. An overview of data usage and the number of mobile phone subscriptions is illustrated in Figure 2. The use of mobile phone signal quality from PODES data will be discussed further in section 3.2.3.

The IFLS summarises and provides complete, detailed, and comprehensive information on demographic, socioeconomic conditions, and behaviour at the individual, household, and community levels. The IFLS was administered in 13 provinces, representing 83% of Indonesia's population. Furthermore, the IFLS is intended to be used as a longitudinal panel or cross-sectional population information (see Strauss, Witoelar & Sikoki 2016). This study will focus on the household level, and more than 6,073 cross-sectional household data is valuable because we will see comprehensively how ICT and its intended use can change household welfare. Meanwhile, longitudinal panel data (4,432 cross-sectional households observed for two time periods) can increase the precision of investigations of how welfare changes are experienced from differences in ICT characteristics between households.



Note: The indicator includes the number of post-paid subscriptions, and the number of active prepaid accounts (i.e., phones that have been used during the last three months)

Figure 2. Number of mobile phones subscriptions per 100 persons in Indonesia, 1997-2016

Source: World Bank from International Telecommunication Union (ITU) World Telecommunication/ICT Indicators

3.2 Estimation Strategy

In this study, the theoretical hypothesis mentioned that, in ceteris paribus, the mobile phone positively affects household welfare due to its gain in human capital, reducing cost transactions, and stimulating work participation. Therefore, a positive relationship between mobile phones and household welfare is anticipated, and this hypothesis is examined by estimating the following cross-sectional specification:

$$Ln\ HHexp_i = \beta_0 + \beta_1 MP_i + \beta_2 MPF_i + \beta_3 X_i + \varepsilon_i \quad (2)$$

Where Ln $HHexp$ is the household welfare of household *i,* measured by the natural logarithm of household expenditure, MP denotes mobile phone use, MPF *is* mobile phone specific function, and X indicates controls for household characteristics and community characteristics. Household characteristics, for instance, household head age in linear and squared form, gender, marital status, education year, dummy employment status (self-employed, private or public worker, freelance, etc.), number of all household members, dummy residence status, the dependency ratio (children and older adult compared to productive ages in the household), dummy loan ownership status, dummy location whether a household in an urban or rural location, dummy whether household access electricity and water condition. The community-level controls include the number of health posts and the dummy of road conditions in the community. The parameter of primary interest is the coefficient β_1, which can be interpreted as the difference between mobile phone users and non-users. Correspondingly, it would be interesting to examine coefficient β_2 to determine the distinct effects of mobile phone functions in the household. Equation 1 is estimated using Ordinary Least Squares for clarity (OLS). Standard errors that are robust to heteroskedasticity are clustered at the household level, and the fifth wave of IFLS is used only because questions about mobile phone availability occur only during this time period of data.

The potential endogeneity of the interest explanatory variable is an important methodological issue (mobile phone). Endogeneity, or the presence of an endogenous variable in a regression equation, may arise for two reasons: an absent variable bias or simultaneous causality bias (Wooldridge, 2002). Omitted variable bias can occur when variables associated with the dependent variable are not considered, resulting in their exclusion from the regression. The dual causality bias is an endogenous issue or the condition when X influences Y and Y influences X. Endogeneity results in a biased and inconsistent estimator.

3.2.1 Endogeneity Issue

To address the issue of endogeneity, the author devised a model comprised of two equations. First, the author adds Equation 3 to describe mobile phone ownership (MP_i^*). Mobile phone ownership is a treatment that is subject to endogenous selection. It is denoted by $MP_i = 1$ and indicates that at least one mobile phone is owned by a household member. $MP_i = 0$ indicates that no mobile phone is owned. The following cross-section function describes the likelihood of smartphone ownership:

$$MP_i^* = \gamma_0 + \gamma_1 z_i + \gamma_2 X_i + v_i \quad with \quad MP_i = \begin{cases} 1\ if\ MP_i^* > 0 \\ 0\ otherwise \end{cases} \quad (1)$$

z_i represents the instrumental variables. In this study, the average ratio of mobile phone users in the subdistrict where the household resides (excluding the household's mobile phone users) is used as an instrumental variable of mobile phone usage in the household. People in the same neighbourhood tend to behave similarly (Yang, 2022). In general, the author anticipates that due to the interaction effect of community behaviour, the mobile phone usage of households within a community will be related to the average usage ratio. Moreover, the author included the proportion of households with electricity, which the author anticipates will have a positive correlation with mobile phones in the event of technology penetration. Previous studies by other researchers used a design that included these instrumental variables. (Dettling, 2017; Hartje & Hübler, 2017; Yang, 2022). X_i represents a vector of control variables that can be found in Equation 1. μ_i signify the binary subdistrict specific effects and v_i is the error terms of the equation 3.

Equation 3's result could be combined by the same linear cross-section outcome as Equation 2. Equations 3 and 2 would be estimated jointly using Endogenous Treatment Regression (ETR) based on (Heckman, 1979). This estimation utilizes the Maximum Likelihood (ML) criterion (Maddala, 1983) letting v_i and ε_i be correlated and bivariate-normally distributed (Cameron & Trivedi, 2005), section 25.3.4). Further, the author uses a Wald Test (Wald χ^2 = 9.16 and P=0.0025) indicates that we can reject the null hypothesis of no correlation between the treatment error (v_i) and linear outcome error (ε_i) (this also add in Appendix A). These findings confirm the ETR is preferable here, defined as complete independence between potential outcomes and treatment (unconfoundedness). Later the estimates also employ standard errors robust to heteroskedasticity and obtained the average treatment effect of mobile phone access to the household expenditures by the estimated β_1.

3.2.2 Quantile Regressions

Additionally, the author noted that mobile phone access has various impacts depending on the household's position in economic welfare distribution. The magnitude, sign, and statistical significance of these effects may vary. When the dependent variable has a large variance, the calculated coefficient in linear regression indicates the influence of the explanatory variable on the average observation (average household welfare), which is not indicative of true household welfare. In this paper,, simultaneous quantile regression approaches are used to account for the various effects of mobile phones on economic welfare across various welfare groups. Quantile regression is expressed as linear functions for simplicity and does not correct for possible endogeneity via instrument variables. Thus, the mathematical equation from Equation 1 would be adept in this quantile regression equation (Koenker & Hallock, 2001):

$$Ln\, HHexp_i = \beta_0 + \beta_1 MP_i + \beta_2 MPF_i + \beta_3 X_i + \varepsilon_i$$
$$with$$
$$Quant_\theta \left(\frac{Ln\, HHexp_i}{MP}\right) = \beta_\theta + \beta_\theta MP_i + \beta_\theta MPF_i + \beta_\theta X_i \qquad (2)$$

The coefficients for mobile phone adoption were derived and compared for various natural logarithms of economic welfare quantiles within a given expenditure defined economic welfare distribution. The calculated coefficients for each population quantile indicate the change in the response variable (welfare) due to a decision in the predictor variable (mobile phone adoption). The estimated parameters reflect the impact of ICT adoption on the welfare of low-income households (those in the bottom quantiles 0.1 of the welfare distribution), middle-class households (those in the quantile 0.5), and the wealthiest households (those in the top quantiles 0.9). Using a series of Hausman specification tests, it is possible to determine whether the differences between the estimated coefficients for the various quantiles are significantly different from zero. Notably, the possibility of explanatory variables is endogenous, consequently, these results are viewed as associations and may not capture any causal effects.

Table 1. Association between mobile phone signal coverage with telecommunication expenditures and mobile phone ownership

Column Number	(1)	(2)
Estimation Method	Linear Probability Model	
Dependent Variable	HH nonzero telecom expenditure	Phone owned
weak signal	0.0260	0.0492
	(0.0221)	(0.0304)
strong signal	0.0531*	0.0609**
	(0.0280)	(0.0305)
Constant	0.220	0.707***
	(0.253)	(0.0633)
Observations	9,154	4,849
R-squared	0.339	0.344
HH Character.	YES	YES
Community Character.	YES	YES
Year FE	YES	NO
Subdistrict FE	YES	YES

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

3.2.3 Signal Quality as Mobile Phone Expansion Measurement

As discussed in the previous section, the use of mobile phones raises the issue of endogeneity and bias in estimating the effect of communication technology expansion. Furthermore, the use of cross-sectional data has inherent limitations due to its selective bias. To address this issue, an alternative approach to measuring differences in regional availability or proximity of new infrastructure is used (Farré & Fasani, 2013; Olken, 2009). The author employs PODES data to assess the expansion of mobile phone infrastructure across Indonesian subdistricts. The PODES data used by the author dates back to 2006. (PODES is not available every year, the closest data available to IFLS 4 in 2017 are PODES 2006). In the data, a village chief or senior civil servant is asked whether the village or urban neighbourhood has a mobile phone signal. Then, classify this signal as strong, weak, or non-existent. From this information, the author defines that the subdistrict level has a strong mobile signal coverage when 100% on average within the village/urban neighbourhoods' level has a strong mobile phone signal. Furthermore, this study defines the subdistrict level as having a weak mobile phone signal when 100% on average within the village/urban neighbourhoods' level has a weak mobile phone signal. This infrastructure design variable was also adapted from recent studies such as Sari & Yudhistira (2021) and Huangfu & Nobles (2022).

The authors use the IFLS to test the association between dummy regional signal coverage quality and two measures of household mobile phone use to provide evidence that regional variation can be an important differentiator in mobile phone ownership and can be used at the household level. These measurements include whether the household spent expenditure on telecommunications between 2007 and 2014, as well as whether the household owns a mobile phone, which is only measured in IFLS 2014. Table 1 shows the results of regressing the two IFLS measurements with dummy subdistrict mobile phone signal coverage quality (without signal in the subdistrict as the based group). The author observes that mobile solid phone signal coverage in the subdistrict is associated with a 5.3% increase in the probability of having telecommunication expenditures and a 6.1% increase in the probability of owning a mobile phone when compared to the subdistrict household with no signal at all. After being justified by household head age and age squared form, education, marital status, residence status, community characteristics, and subdistrict fixed effects, this estimation was implemented.

3.2.4 Two-way Fixed Effect

Based on the earlier measurement, the author could now utilise both longitudinal IFLS 4 and 5 datasets. Other terms utilised a large cross-section of individuals observed over a few time periods, but its primary benefit is increased estimation precision (Cameron & Trivedi, 2005). The second advantage of panel data is the potential for consistent estimation of the fixed effect model which permits unobserved individual heterogeneity that may correlate with regressors. Consequently, it establishes causality with weaker assumptions than cross-section or panel data without fixed effects, such as pooled and random effects models (Wooldridge, 2002). The two-way fixed effect equation could illustrate with the following equation:

$$Ln\, HHexp_{it} = \beta_0 + \beta_1 MPS_i + \beta_2 X_{it} + \gamma_t + \mu_i + \varepsilon_{it} \quad (5)$$

The distinction between Equation 5 and Equation 2 is now in μ_i which represents the household fixed effect, and γ_t which represents the time fixed effect. The fixed effects model has some practical shortcomings, such as the inability to calculate the coefficient of a time-invariant regressor, such as gender, because it is absorbed by the individual-specific effect. In addition to Equation 2, the author uses control variables to represent household and community characteristics in order to determine the impact of mobile phone signal expansion on household expenditure. The author adopts the panel data regression quantile adopting approach developed by Machado and Silva (2019) in order to provide additional evidence of potential impacts based on the household's position in the economic welfare distribution. The author would examine the coefficient of mobile phone signal quality within the group of household expenditures.

4. Results

Table 2 displays the findings of this study's variable interest with the household expenditures and the household expenditure distribution. According to Thornton & Innes (1989), the proportional effects of discrete variables, such as mobile phone access, on natural logarithm household expenditure are calculated using the formula $b_1 = [\exp(\beta_1) - 1]$, where β_1 is the coefficient of the variable. The results of OLS and ETR's estimates of the effects of mobile phone access on household expenditure are shown in columns 1 and 2. The OLS results indicate that households with mobile phone access have 10.2% (exp[0.0998]-1) larger household expenditures than those without mobile phone access. In contrast, the ETR estimation results indicate a higher result, that is 74.3%. (exp[0.554]-1). It is possible for the ETR estimate to be greater than the OLS estimate due to the fact that the ETR estimates the local average treatment effect (LATE). In other words, the ETR estimate the effect of treatment only for the observable whose choice of treatment was influenced by the instruments, whereas the OLS estimate describes the average difference in household expenditures for those with different mobile phone access (see Cameron and Trivedi 2005 section 25.7.1).

The quantile regression results are shown in columns 3 through 5. The coefficient of the variable measuring mobile phone access is positive and statistically significant at the quantiles reported. The magnitude of the coefficient increases monotonically per quantile and it is indicating that mobile phone access benefits Indonesian households with higher household expenditures the most. For example, the increase in household expenditure at the 0.1 quantile for households that have used mobile phones is approximately 8.8% (exp[0.085]-1) compared to households without mobile phone access. At higher quantiles 0.9, the mobile phone increases household expenditures by as much as 10.4%. (exp[0.099]-1). In terms of mobile phone uses, it can be observed that the difference between quantiles for the use of mobile phones for business is greater than that for communication. Quantile 0.1 is 7.3% (exp[0.071]-1) and quantile 0.9 is approximately 22.5% (exp[0.203]-1). Figure 3 also demonstrates this difference in magnitude. The results of OLS, ETR, and quantiles regression are shows after adjusted with household characteristics such as household head age, age quadratic form, gender, marital status, education, and employment status. Moreover, it is also adjusted with the regional characteristics such as household size, residency status, dependency ratio, household member loan status, urban or rural region, household access to electricity, piped water, asphalt road, and health post.

In addition, the effects of mobile phone signal quality on household expenditure have been estimated using the two-way fixed effect model depicted in Table 2, column 6. Consequently, a weak signal in the subdistrict has a positive and statistically significant effect on household expenditure (5.7% [exp(0.058)-1]) relative to households without a signal. The quantile regression data panel in columns 7-9 indicates the subdistrict's weak signals are uniformly positive and statistically significant across quantiles 0.5 and 0.9. Specifically, a weak mobile phone signal increases household expenditures by 5.9% (exp[0.058]-1) at the quantile 0.5 and by 10.1% (exp[0.096]-1) at the quantile 0.9. Nevertheless, as shown in Figure 4, all quantile estimations within the quantiles group vary within the fixed effect confidence interval (upper bound and lower bound). Thus, the difference between fixed quantile estimation and overall fixed effect estimation is not differently significant. In addition, estimates for all control variables have the expected signs, although some variables are not statistically significant. The results appear after adjusted with the household characteristics, regional characteristics, household fixed effect, and year fixed effect (2007).

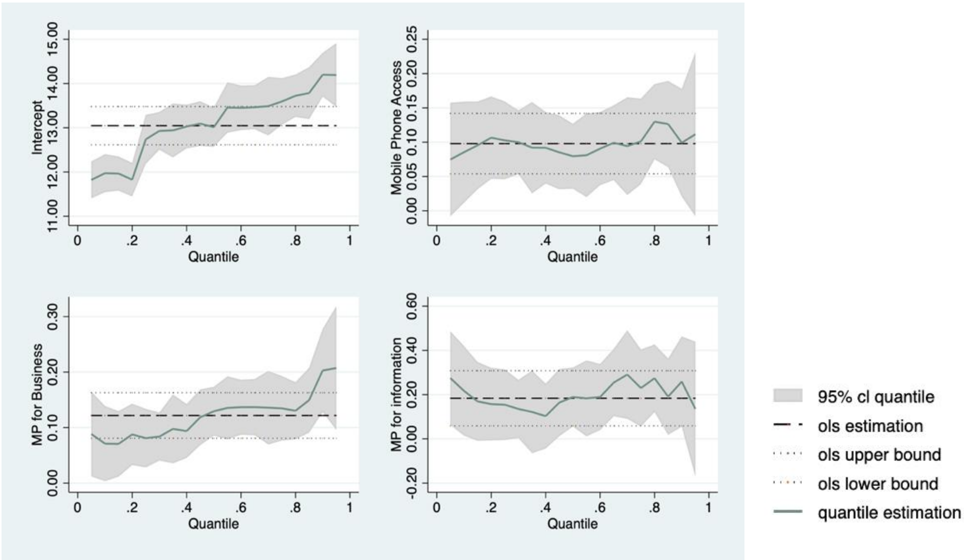


Figure 3. Quantiles regression estimates for intercept, mobile phone access, mobile phone for business and information on natural logarithm household expenditures in Indonesia, 2014

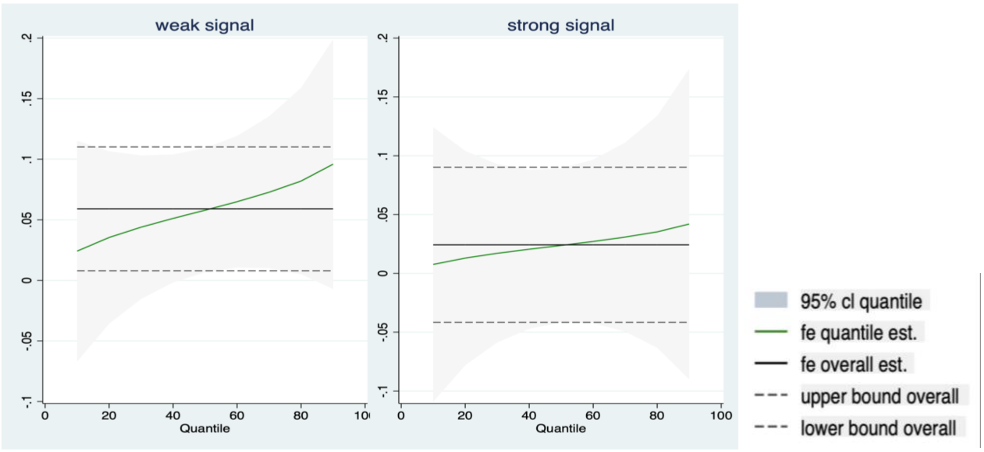


Figure 4. Panel quantiles regression estimates for weak signal and strong signal on natural logarithm household expenditure in Indonesia, 2007 and 2014

Table 2. The impact of mobile phone access and signal quality on household expenditures and the variance in household expenditure distribution

Column Number	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimation Method	OLS*	ETR (ML)*	Quantile 0.1	Quantile 0.5	Quantile 0.9	Fixed Effect	FE Quantile 0.1	FE Quantile 0.5	FE Quantile 0.9
Dependent Variable	Ln HH Exp	Ln HH Exp	Ln HH Exp	Ln HH Exp	Ln HH Exp	Ln HH Exp	Ln HH Exp	Ln HH Exp	Ln HH Exp
Mobile Phone access	0.098***	0.554***	0.085**	0.079***	0.099***				
	(0.022)	(0.0419)	(0.037)	(0.024)	(0.034)				
MP Purposes									
(Base: for communication)									
MP for entertain	0.024	0.0221	0.029	0.019	-0.010				
	(0.018)	(0.0180)	(0.028)	(0.021)	(0.023)				
MP for business	0.122***	0.125***	0.071**	0.129***	0.203***				
	(0.020)	(0.0202)	(0.032)	(0.023)	(0.030)				
MP for information	0.184***	0.178***	0.217***	0.189***	0.259**				
	(0.055)	(0.0572)	(0.057)	(0.071)	(0.116)				
Signal Quality (Base: no signal)									
weak signal						0.056**	0.024	0.058**	0.096*
						(0.024)	(0.046)	(0.026)	(0.053)
strong signal						0.041	0.008	0.024	0.042

Column Number	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimation Method	OLS*	ETR (ML)*	Quantile 0.1	Quantile 0.5	Quantile 0.9	Fixed Effect	FE Quantile 0.1	FE Quantile 0.5	FE Quantile 0.9
Dependent Variable	Ln HH Exp	Ln HH Exp	Ln HH Exp	Ln HH Exp	Ln HH Exp	Ln HH Exp	Ln HH Exp	Ln HH Exp	Ln HH Exp
						(0.030)	(0.059)	(0.033)	(0.067)
Constant	13.04***	12.82***	11.97***	13.01***	14.19***	12.30***			
	(0.246)	(0.246)	(0.273)	(0.509)	(0.181)	(0.543)			
Observations	6,120	6,073	6,120	6,120	6,120	8,864	8,864	8,864	8,864
R-squared	0.344		0.2177	0.1913	0.1777	0.662			
HH Character.	YES	YES	YES	YES	YES	YES	YES	YES	YES
Region Character.	YES	YES	YES	YES	YES	YES	YES	YES	YES
HH FE	NO	NO	NO	NO	NO	YES	YES	YES	YES
Year FE	NO	NO	NO	NO	NO	YES	YES	YES	YES

Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: OLS (Ordinary Least Square); ETR (Endogenous Treatment Regression) with ML (Maximum Likelihood)

The author employs the Breusch & Pagan (1979) and Cook & Weisberg (1983) approaches to test heteroskedasticity (hettest) for OLS estimation in the robustness check. The result of hettest indicates that the model rejects the null hypothesis that it lacks evidence from heteroskedasticity. Nevertheless, heteroskedasticity is unavoidable in OLS estimation, and quantile regression is part of the heteroskedasticity issue's correction. In another test, the author attempts to resolve the Wald robustness check, which is already explained in section 3.2.1, for the ETR robustness check. Finally, another robustness check was performed on the two-way fixed effect model for panel data. First, the author employs Breusch and Pagan's (1980) Lagrange Multiplier (BPLM) test for a random effect, or it is testing the null hypothesis var $(\mu_i) = 0$; The BPLM test reveals that $\mu_i \neq 0$ as a result. Second, the Hausman specification test is utilised to determine the model's efficacy and whether a systematic difference in coefficient exists between random effect and fixed effect estimation. The Hausman test indicates a statistically significant difference; therefore, the fixed effect model is preferred.

5. Conclusion and Recommendation

This study investigates the effects of mobile phone expenditure on household economic welfare in Indonesia, as measured by household expenditures. The study employed an ETR model to address the endogeneity issue related to mobile phone use. Then, since the OLS and ETR model can only estimate the mean-based effect of mobile phone use on household expenditure, a quantiles regression model was employed to estimate the heterogeneous effects of mobile phone use across the entire distribution of household economic welfare. In 2014, the OLS, ETR, and Quantile Regression models utilised only cross-sectional IFLS 5 data. In order to improve estimation precision, this study develops a two-way fixed effect model by combining PODES data with longitudinal IFLS 4 and 5 data from 2007 and 2014 to examine the impact of subdistrict-level mobile phone signal quality on household expenditures.

The OLS and OTR model found, after controlling for several household and community characteristics, that mobile phone access had a positive linear effect on household welfare in several studies (Muto & Yamano 2009; Zanello 2012; Aker & Mbiti 2010). The estimated results of the quantiles regression model indicated that mobile phone access benefited the upper distributions of household expenditures the most, particularly those households that claimed to use mobile phones for business purposes. This finding indicates that mobile phones play a significant role in determining the distribution of household welfare, with the greatest impact on the top group. It is enhanced differently than previous research by de Silva & Zainudeen (2007) and Tadesse & Bahiigwa (2015). In addition, to pursue broader data, the two-way fixed effect panel model with additional quantiles model indicates that the arrival of mobile phone infrastructure (signal) also increased the average household's economic welfare.

The findings have important policy implications for Indonesia, which has one of the world's largest populations, a diverse archipelago, and a mobile telecommunications industry that exploded in the early 2000s. The positive effects of mobile phones on the economic welfare of households in Indonesia emphasize the importance of promoting a policy that enhances mobile phone penetration and its supporting infrastructure to reduce the cost of provider services, particularly for the underdeveloped group of welfare. In addition, there should be an intervention to promote education on digital awareness and literacy in low-expenditures households. It is expected from the theories that there will be an increase in optimal mobile phone usage for economic capital capacity, cost efficiency, and household work participation in in this vulnerable group.

Despite the fact that the author can use the new infrastructure variable at the subdistrict level, which is merged into a longitudinal data panel, the data is still reliant on reports from the village chief or local senior citizen.

Future research may include a more particular mobile infrastructure with a narrower scope, such as the number of base trans-receiver signal towers at the village level. However, mobile technological equipment such as mobile phones remain indispensable for observing the specific consequences of direct impacts on the economic conditions of households. It is anticipated that future longitudinal studies with longer time periods and direct mobile phone effects will clarify this association.

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