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Access to Fintech and Poverty : Evidence from the Arrival of 4G Networks in Indonesia

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Warwick-Monash Economics Student Papers

December 2021 No: 2021-24

ISSN 2754-3129 (Online)

https://warwick.ac.uk/fac/soc/economics/research/wmesp/

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Jeremy Smith (Head of the Department of Economics, University of Warwick) and Michael Ward (Head of the Department of Economics, Monash University)

Recommended citation: Fatkhurrohman. (2021). Access to Fintech and Poverty: Evidence from the Arrival of 4G Networks in Indonesia. Warwick Monash Economics Student Papers 2021/24.

[1] Warwick Economics would like to thank Lory Barile, Gianna Boero, and Caroline Elliott for their contributions towards the selection process.

Access to Fintech and Poverty: Evidence from the Arrival of 4G Networks in Indonesia

By Fatkhurrohman*

Abstract

This paper investigates the effect of the arrival of 4G networks on poverty rates by exploiting the gradual adoption of 4G networks in 514 districts/cities in Indonesia. Robust differences-in-differences estimates indicate that 4G network adoption has a significant negative influence on poverty rates – which we argue is due to the increased access to Fintech afforded by the 4G network, thus increasing poor people's access to credit. Moreover, Fintech capitalizes on mobile app-based services, a vastly growing business that has gained popularity since 2015. In addition, this paper also finds that Fintech promotes internet-based job opportunities for impoverished individuals, increasing their income and alleviating poverty in Indonesia.

JEL *Classification*: O33, O36, O53, I31, I32

Keywords: Fintech, Financial Inclusion, Poverty, Welfare, Indonesia

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I would like to convey my gratitude to Stefano Caria for his numerous comments, insights and great discussions. I am indebted to *Bank Indonesia* and *Kominfo* – *Republic of Indonesia* for providing me with the necessary data. Finally, I would like to thank my family for their endless support during this difficult period.

1. Introduction

Poverty reduction has gone global with the UN's 2030 Agenda for Sustainable Development. Many emerging countries have taken social initiatives to help the underprivileged. However, the returns on various government investments are unclear, especially in new technologies. Therefore, this study aims to fill this gap by investigating the influence of 4G network adoption on poverty.

Despite solid economic growth since the 1997–1998 Asian Financial Crisis, Indonesia faces numerous challenges. For instance, rising inequality has hampered the government's anti-poverty plan. The Gini coefficient climbed from 0.31 in 2000 to 0.43 in 2013. Mining, industrial crops, telecommunications, and financial services have grown faster than agriculture and manufacturing, which employ roughly 35% of the workforce (Aji, 2015). Economic growth thus benefits wealthy owners of the former sectors, increasing inequality.

In 2010, the government established The National Team for the Acceleration of Poverty Reduction (TNP2K) to address the issue. Between 2010 and 2015, the team helped create an integrated poverty database, expanded *Program Keluarga Harapan (PKH)*[2], and introduced *Kartu Keluarga Sejahtera (KKS)*[3]. However, the poverty incidence fell dramatically from 2006 to 2010 but has not fallen as quickly in the subsequent four years.

Table 1 - Poverty Incidence in Indonesia, 2006 – 2014

	2006	2007	2008	2009	2010	2011	2012	2013	2014
Relative Poverty (% of population)	17.8	16.6	15.4	14.2	13.3	12.5	11.7	11.5	11.0
Absolute Poverty (in millions)	39	37	35	33	31	30	29	29	28
Rural Poverty (% living below rural poverty line)	21.8	20.4	18.9	17.4	16.6	15.7	14.3	14.4	13.8
Urban Poverty (% living below urban poverty line)	13.5	12.5	11.6	10.7	9.9	9.2	8.4	8.5	8.2

Source: BPS-Statistics Indonesia, retrieved from ADB Papers

As shown in Table 1, economically disadvantaged people live in rural areas where infrastructure is lacking. Papua (27.8%), West Papua (26.3%), East Nusa Tenggara (19.6%), Maluku (18.4%), Gorontalo (17.4%) and West Nusa Tenggara (17.1%) had the highest poverty rates in 2014. Moreover, rural areas have fewer employment options; thus, people are self-employed or work in agriculture. As a result of increased access to jobs and information, urban residents earn more.

The aforementioned reasons combined with the implementation of the 2030 United Nations Sustainable Development Goals (SDG) motivate the government to restructure

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[2] *Program Keluarga Harapan (PKH)* or the Family Hope Program is a conditional cash transfer program initiated by the government for very poor households in Indonesia.

[3] *Kartu Keluarga Sejahtera (KKS)* is an identification card issued by the government for economically disadvantage households.

the poverty alleviation strategy in RPJMN 2015–2019.[4] One of the new framework's critical objectives is to promote inclusive economic growth and reduce the national poverty rate to 6%– 8% by 2019.

Parallel to the new framework for combating poverty, the government strengthened rural connectivity and accelerated infrastructure development. After completing the 1.800 MHz frequency band reframing in November 2015, the Ministry of Communication and Information Technology *(Kominfo)* collaborated with several major telco providers (including *Indosat, XL,* and *Telkomsel*[5]) to deliver the 4G network, improving mobile phone and internet access across the country. By the end of 2015, the 4G network had covered 42 cities/districts (*Kominfo*, 2015). The number of districts/cities covered continued to grow, reaching 145 in 2016 and 412 in 2017, out of 514 districts/cities in Indonesia.

4G networks have improved internet connectivity. In this situation, people will have equal access to information, thus eliminating asymmetric information and increasing market efficiency. Many believe that widespread internet access could boost innovation, job creation, and inclusive economic growth. In addition, the internet will allow the financial services industry to reach the financially excluded in rural areas as Financial Technology (Fintech) emerges in Indonesia. With one tap, they can access financial products and services through their mobile phones.

For instance, Akhmad, a father of three children with no degree, wakes up in his home in Papua,[6] opens his mobile phone and borrows £10 from his Fintech lending application, which offers a lower borrowing rate than unregistered moneylenders. During the day, he uses the money to purchase petrol for his motorcycle, to provide taxi and food delivery services via his *Gojek*[7] app. After work, he uses his *goPay*[8] to settle his debt with his Fintech lender, buy groceries and other household necessities from *GoFood* merchants and save the rest in *goPay*. That is a simplified illustration of how equitable access to information and communication technology (ICT) creates a serial chain of economic transactions that powers the economy.

Surprisingly, studies investigating ICT and Fintech impacts on poverty are scarce. To the author's knowledge, very little research has ever been done on ICT, Fintech and poverty in Indonesia. Existing research on internet access and employment do not explain how employment gains reduce poverty (Hjort & Poulsen, 2019; Kusumawardhani, Pramana, Saputri, & Suryadarma, 2021). In another study, Ayse et al. (2020) use panel data from various countries to investigate the links between Fintech, financial inclusion, and income inequality. Therefore, the impact of increased access to

[4] RPJMN stands for National Medium-Term Development Plan (*Rencana Pembangunan Jangka Menengah Panjang*), which elaborates the 5 years development plan according to the chosen President at the period. RPJMN 2015-2019 was proposed by President Joko Widodo and known as Nawacita.

[5] Three big telco providers in Indonesia.

[6] Papua is one of the province in the Eastern Indonesia, with the highest poverty incidences as of 2014.

[7] *Gojek* is a technology company that serves transportation through motorcycle taxi service, which then expand to private hire service, food delivery, bills payment, etc.

[8] Mobile money owned by *Gojek*, which can be used as payments.

Fintech (measured by mobile phones and internet usage for financial transactions), following the launch of the 4G network, on poverty in Indonesia is examined in this study. This paper aims to address two main questions: (i) does 4G network adoption reduce poverty in Indonesia, and (ii) is the poverty-reduction impact of 4G networks driven by increased Fintech adoption?

This study employs a difference-in-difference (DiD) approach on the district-level panel dataset, constructed from the 2015–2019 National Socio-Economic Survey *(Susenas)* to investigate the theoretical hypothesis. The emergence of 4G networks is beneficial for poverty reduction in Indonesia via increased Fintech usage. Conditional on the district, year and regional trend fixed effect, 4G networks decreased poverty by 0.231 ppts in the treatment districts compared to the control districts, and this result is robust to various validity checks. In the absence of Fintech effects, the impact decreases from 0.231 to 0.192 and becomes statistically insignificant, confirming the mediating effect of Fintech. This study also reveals that the proliferation of mobile app-based services (i.e., *Gojek Apps*) also contributes to poverty reduction by increasing employment in the related sectors.

The remainder of this paper is structured in the following manner: Section 2 conducts a review of the pertinent literature on ICT, Fintech, financial inclusion and poverty, Section 3 explains the identification strategy and model specifications, Section 4 describes the dataset, Section 5 discuss the results, Section 6 describes the validity and robustness checks, and finally, Section 7 summarizes the findings.

2. Literature Review

It was widely known that financial development promotes economic growth and reduces poverty. However, the evidence on the impact of financial access on welfare is mixed. Meanwhile, another strand of studies found a connection between ICT availability, market outputs, and welfare.

2.1 Financial Inclusion and Poverty

Many economists argue that poor people remain poor for two reasons: (i) disparity in opportunities and (ii) disparity in fundamentals. According to the first view, disparities in opportunities (including access to information, jobs and financial services) lead to unequal income distribution between developed and developing regions. The poverty trap models demonstrated that in the presence of an imperfect credit market, poor households could not borrow to start their own business or invest in their children's education (Galor & Zeira, 1993; Banerjee & Newman, 1993; Balboni, Bandiera, Burgess, Ghatak, & Heil, 2020). As a result, financial provision was perceived as the primary solution. However, there was conflicting evidence on this point. Several studies discovered a link between financial inclusion, income equality and poverty reduction (Sahay, et al., 2015; Mohammed & Gyeke-dako, 2017; Park & Mercado, 2018; Zhang & Posso, 2019; Ayse, Pesqué-Cela, Altunbas, & Murinde, 2020). Financial access enables households to smoothen their consumption patterns, while firms can invest and increase their capital over time, increasing their business and improving people's welfare. Additionally, Bruhn and Love (2014) exploit Mexico's new Banco Azteca as a natural experiment; they show that increased financial access help to alleviate poverty by affecting labour market activity and income levels.

Certain studies, however, cast doubt on the effect of increased financial access on household income and poverty (Banerjee & Duflo, 2007; Kochar, 2011; Dupas, Karlan, Robinson, & Ubfal, 2018). Kochar (2011) discovered that banking infrastructure expansion in rural India does not equally impact poor and rich households; wealthier households benefit more, resulting in increased inequality. Dupas et al. (2018) argue in another study, using the data from Uganda, Malawi and Chile, that simply expanding access to basic accounts will likely not be sufficient to broaden the financial access, increase downstream outcomes and provide hope for poverty alleviation. They also suggest that products with lower transaction costs (such as saving accounts linked to mobile money or saving-led microfinance groups) might be more appealing (Dupas et al., 2018).

Therefore, past shreds of evidence show that different dimensions of financial inclusion have distinct effects on poverty, and the effect might vary over time across individuals and regions. This study contributes to this literature strand by providing micro evidence on the relationship between financial inclusion and poverty in emerging economies.

2.2 Access to ICT, Fintech and Poverty

Meanwhile, ICT has grown faster over the last decades, increasing access to information and services, reducing price disparities and promoting economic development (Jensen, 2007; Aker & Mbiti, 2010; Beuermann, McKelvey, & Vakis, 2012). Eight out of ten people in developing countries own a mobile phone (World Bank, 2016). As a result, many indicate that ICT, including Fintech, help to close the gap in financial access for low-income households and small businesses, increasing financial inclusion and reducing inequality and poverty (Ayse et al., 2020; Appiah-Otoo & Song, 2021).

According to Alliance for Financial Inclusion (2018), recent waves of financial technology have been hailed as new innovative ways to alleviate poverty, building on the Fintech success story in Kenya, China and India. Indeed, the expansion of innovative digital financial services is viewed as a critical driver of financial inclusion. It helps the unbanked population gain access to financial services, contributing to more inclusive growth (GPFI, 2017).

Additionally, the channel through which ICT and Fintech affect poverty is worth discussing; theoretically, many have proposed three main channels: (i) financial inclusion, (ii) financial development and (iii) economic growth. First, it is widely recognized that ICT and Fintech increase financial inclusion. Fintech enables households and small businesses to access funds quickly compared to traditional banks. Poor households and MSMEs are unlikely to have sufficient assets and consistent cash flow, preventing them from obtaining collateralized bank loans (Goldin, 2014).

Second, ICT and Fintech have the potential to alleviate poverty via financial development. According to a recent study by Meifang, He, Xianrong, & Xiaobo (2018), Fintech benefits China's financial sector by boosting its size, profitability and security. At the same time, another study conducted by Feyen, Frost, Gambacorta, Natarajan, & Saal (2021) claims that improvements in connectivity and computing could improve efficiency. While this might not be accomplished yet, different products and services have been unbundled in the financial and banking sectors.

Finally, increased access to internet services can generate new jobs and income opportunities for the poor (Jensen, 2007; Aker & Mbiti, 2010; Beuermann, McKelvey, & Vakis, 2012). ICT and Fintech encourage e-commerce and technological-based startups to rise, improving households' income while opening access to loans and reducing their risks to shocks (Bharadwaj, Jack, & Suri, 2019). Eventually, it improves household consumption and saving, reducing poverty. Using data from 12 African countries and the gradual arrival of ten submarine internet cables from Europe, Hjort and Poulsen (2019) demonstrate that access to a faster internet connection affects employment and income in Africa. Improved internet connectivity expands access to and decreases the cost of information and communication, thus reducing employment inequality. In another study, Kusumawardhani et al. (2021) show that internet availability increases women's probability of getting full-time jobs in Indonesia.

However, the micro-level evidence on ICT, Fintech and poverty is relatively scarce. This reason, combined with the contradictory evidence regarding the effect of financial inclusion on poverty and the waves of new internet-based jobs in Indonesia, motivates the author to examine further the impact of ICT and Fintech on poverty in Indonesia. This study will contribute to this strand of literature by providing evidence on how ICT and Fintech can help to reduce poverty in Indonesia.

3. Empirical Strategy

To assess the ICT and Fintech effect on poverty in Indonesia, this study exploits the variation of 4G network adoption in 514 districts/cities. The districts/cities are categorized into treatment groups (covered by 4G networks) and control groups (not covered by 4G networks), and then the change in poverty rates for the treatment and control districts/cities is examined.

In 2015, the 4G network was launched in 42 locations throughout Indonesia. By the end of 2016, the 4G network had covered 145 large districts/cities, and it increased to 412 districts/cities in 2017. Although the government regulates the internet and telecommunication industry, the network is supplied by private providers; consequently, it is undoubtedly influenced by the profitability of each district/city from the companies' perspectives. They first commence from big cities/districts and work their way down to less developed areas. This study focuses exclusively on the 369 districts/cities that had not received the 4G network by the end of 2016, to reduce the selection bias caused by the difference in districts/cities characteristics.

The primary hypothesis is that the treatment will reduce the poverty rates in the treatment group relative to the control group. Therefore, the following DiD equation is estimated:

$$Pov_{dt} = \beta_0 + \beta_1\, 4GNet_{dt} + \beta_2\, POST_t + \beta_3\, (4GNet * POST)_{dt} + \boldsymbol{\gamma_i X'_{idt}} + \varepsilon_{dt} \qquad (1)$$

$$4GNet_{dt} = \begin{cases} 1 & -\ districts/cities\ with\ 4G\ network \\ 0 & -\ otherwise \end{cases}$$

$$POST_t = \begin{cases} 1 & -\ after\ 2017 \\ 0 & -\ before\ 2017' \end{cases}$$

where Pov_{dt} denotes the poverty rate in district d at a given point in time. $4GNet_{dt}$ is a dummy variable that is set to one if district/city is covered by the 4G network and zero otherwise. $POST_t$ is time dummy with a value of one for the period following 2017, and X'_{idt} is the vector of time-varying control variables correlated with poverty. In this design, β_3 is the coefficient of interest; it explains the average treatment effect on the treatment group compared to the control group. However, while the simple DiD framework in (1) is quite effective at examining the difference between two groups, it does have some limitations. Firstly, it overlooks the possibility that the treatment effect might vary according to the district's characteristics and time-varying unobservables. For instance, districts with varying geographical locations are likely to receive distinctive 4G network signals or have contrasting populations who use internet/mobile phones, altering the impact of 4G networks on poverty. Secondly, the design examines only two time periods: before and after the treatment. One could argue that the treatment effects may change over time.

To address the concerns above, a framework of generalized DiD developed by Bertrand, Duflo & Mullainathan (2004), Hansen (2007) and Callaway & Sant'Anna (2020) is adopted. The generalized DiD employs multiple periods before and after the treatment with a year-fixed effect to address the time trend effect. Additionally, the district fixed effect is imposed in the DiD equation to account for the district's time-invariant effect. When pre-and post-treatment periods are added, the DiD equation becomes:

$$Pov_{dt} = \lambda_t + \theta_d + \beta_1\, 4GNet_{dt} + \beta_2\, POST_t + \beta_3\, (4GNet * POST)_{dt} + \boldsymbol{\gamma_i X'_{idt}} + \varepsilon_{idt,} \quad (2)$$

where λ_t denotes the year effect, θ_d denotes the district fixed effect and X'_{idt} denotes the vector of time-varying control variables that create potential bias such as population, literacy rate, access to electricity, access to adequate sanitation, access to safe water, percentage of people living in rural areas and percentage of people receiving government transfers. In addition, estimating β_3 is of our interest where the poverty rate was expected to be lower in districts covered by 4G networks (i.e. treatment districts). Standard errors for all regressions are clustered at the district level.

Another concern in determining the causal effect is Indonesia's geographical location. Indonesia is divided into six major islands/regions; Java, Sumatera, Kalimantan, Sulawesi, Maluku and Irian, and Bali and Nusa Tenggara. These major islands differ in various dimensions, including their location within the Palapa Ring[9] project's backbone network development and the timing of their connection. Consequently, the region-year trends are added into the model, resulting in the following regression:

$$Pov_{dt} = \lambda_t + \theta_d + (\alpha * year)_{rdt} + \beta_1\, 4GNet_{dt} + \beta_2\, POST_t + \beta_3\, (4GNet * POST)_{dt} + \boldsymbol{\gamma_i X'_{idt}} + \varepsilon_{idt}, \quad (3)$$

where $(\alpha * year)_{rdt}$ denotes the region-year effect, which captures the time-varying geographical trends.

That being said, the accuracy of the DiD framework is highly dependent on the plausibility of the parallel trend assumption (Bertrand, Duflo, & Mullainathan, 2004; Angrist & Pischke, 2008). In other words, in the absence of treatment, the poverty rates of the treatment and control groups are required to follow a common trend. Figures 1 and 2 below show the visual evidence supporting the parallel assumption of the poverty rate and Fintech in the treatment and control groups before the 4G network adoption. It can be observed that in the absence of treatment, the poverty rate and Fintech in both groups seem to evolve in similar ways. However, relying solely on the graph is not appropriate to assume that there are no pre-trends in the treatment group prior to the adoption period, conditional on control variables. Therefore, another parallel trend test is performed in Section 6 to ensure the validity of the DiD method.

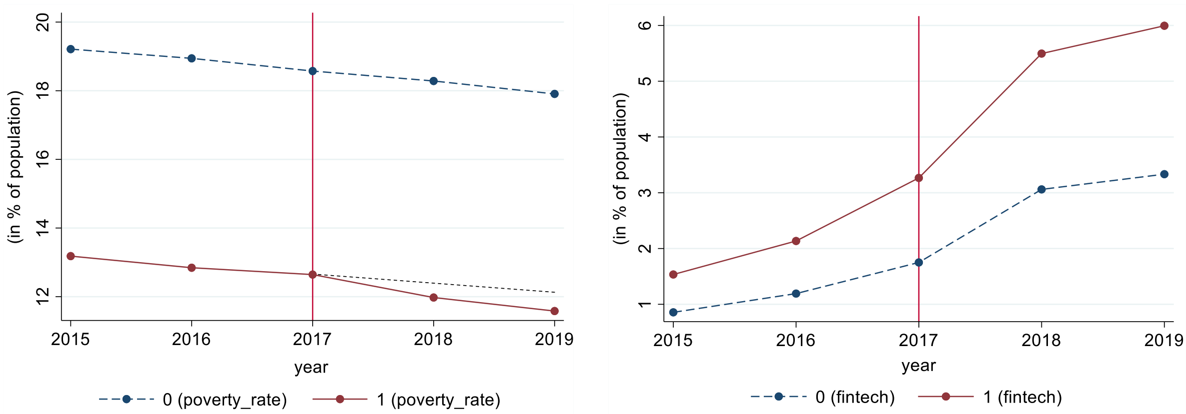

Figure 1. Parallel trends of poverty rates and Fintech between treatment and control group

[9] The Palapa Ring, sometimes referred to as the Sky Toll Road, is a national fiber optic network development project which reaches all the 34 provinces and 440 districts/cities in Indonesia. The provision of fiber optic network aims to develop one of the government's effort to meet 2015–2019 National Medium Term Development Plan (Medina, 2020).

To determine the mediating effect from 4G network adoption, Fintech and poverty rate, equations (2) and (3) are estimated with a set of potential mediators on the left-hand side (LHS), including (i) percentage of people who use Fintech (Fintech), (ii) percentage of people who have access to credits (credit), (iii) percentage of people who have saving accounts (saving) and (iv) the percentage of people working in service industries.

Additionally, this paper also follows Acharya, Blackwell, & Sen (2016) two-stage procedure to identify the mediation. In the first stage, the poverty rate, Fintech and a set of controls are estimated to obtain the expected Fintech effect on poverty. The residuals are obtained from the first regression, fixing Fintech at some given level. The residuals from the first regression can be used to estimate the demediated effect of 4G networks on poverty: the effect of 4G networks on poverty that does not come from an increase in Fintech. A comparison of the demediated effect and the original effect is informative of the importance of the mediator.

4. Data and Variables

4.1 Data Sources

The district-level data is derived from the 2015–2019 National Socioeconomic Survey *(Susenas)*. *Susenas* is an annual survey conducted by Statistics Indonesia that reaches over 250.000 households across 34 provinces (514 districts) in the country. It amasses detailed information on consumption, communication, education, migration, labour, health and household characteristics.

The 4G network coverage data in 2016–2017 from the Ministry of Communication and Technology *(Kominfo)* divides the districts/cities into treatment and control groups. Additionally, *Gojek* services coverage data in 2016, 2017 and 2018 from the *Gojek* website publications are utilized to determine whether the districts/cities have *Gojek* services in their areas.

In addition, the village potentials survey *(Podes)* in 2018 is adopted for the robustness checks. *Podes* enables us to attain the cellular signal type (GSM, 3G or 4G) data for every village in Indonesia.

4.2 Variables

All the variables inspected in the paper are presented as follows:

Table 1. Variables Definition

Variable name	Definition	Unit
Panel A: Main dependent variables		
Poverty_rate	Percentage of people living below the national poverty line in each district/city	% of population
Panel B: Fintech indicators		

Variable name	Definition	Unit
Fintech	Share of people utilizing mobile phones and the internet for financial transactions (buy/sell goods and services, e-banking and product/service information)	% of population
Panel C: Financial Inclusion indicators		
Saving	Percentage of people who have saving accounts	% of population
Credit	Percentage of people who have access to credits (from banks and other financial institutions)	% of population
Panel D: Employment in service industry indicators		
Tradefoods_emp	Percentage of people working in the trade, hotel, food and restaurants	% of population
Transcom_emp	Percentage of people working in transport, communication, and IT services	% of population
Finance_emp	Percentage of people working in financial and insurance services	% of population
Other_emp	Percentage of people working in other service industries	% of population
Explanatory variables		
Post	Adoption year dummy: equal to 0 before 2017 and equal to 1 after 2017	/
4GNet	4G network adoption dummy: equal to 0 for the control group and 1 for the treatment group	/
Post*4GNet	The DiD variable	
Panel E: Control variables		
Literacy rate	Percentage of people able to read or write	% of population
Access to electricity	Percentage of people gaining access to electricity	% of population
Access to safe water	Percentage of people having access to safe water	% of population
Access to good sanitation	Percentage of people gaining access to good sanitation	% of population
Working-age population	Percentage of people at the age of 15 or older	% of population
Pov alleviation	Percentage of people receiving transfer programs from the government	% of population
Rural pop	Percentage of people living in rural areas	% of population
Geo	Geographical location dummy with values: 1 – *Java, Bali and Nusa Tenggara*, 2 – *Sumatera*, 3 – *Kalimantan*, 4 – *Sulawesi*, and 5 – *Maluku and Irian*	/

4.2.1 Dependent Variable

The primary explained variable is the poverty rate, defined as the share of people living below the national poverty lines.[10] The national poverty lines serve as a reference point for estimating poverty indicators consistent with the country's specific economic and social circumstances. It reflects local perceptions of the necessary level and

[10] Indonesia's national poverty line is set at the monthly consumption of £20 per person, lower than the international poverty line (around £43 per month per person).

composition of consumption or income to avoid poverty (World Bank, 2021). For this study, the poverty rate calculation method from Statistics Indonesia is employed:

$$Pov_d = \frac{1}{n_d} \sum_{i=1}^{q} \left[\frac{z_d - y_{id}}{z_d}\right]^{\alpha}, \tag{4}$$

where z_d denotes the national poverty line, q denotes the number of people living below the national poverty line, y_{id} denotes the average monthly per capita consumption of those living below the poverty line, n_d denotes the population and $\alpha = 0$.

The national poverty line (z_d) is calculated:

$$z_d = fNPL_d + nfNPL_d, \tag{5}$$

where $fNPL_d$ is the national poverty line from food and $nfNPL_d$ is the non-food national poverty line. Both variables are calculated from the annual *Susenas*.

4.2.2 Main Variables of Interest

The primary explanatory variables in this study are two dummies: first, *4GNet* – a treatment dummy that separates the treated and control groups. Districts/cities that have at least 50% of their land area covered by the 4G network are considered treated, while the remaining districts are considered as the control group. Second, *Post* – the year dummy reflects the adoption of the 4G network. Although the 4G network was launched in November 2015, 2017 is chosen as the treatment year to mitigate the bias effect caused by 145 urban cities/districts, which is significantly different from the remaining districts/cities. Existing papers set staggered timing of adoption when the treatment group is not treated simultaneously (Beuermann, et al., 2012; Callaway & Sant'Anna, 2020). However, since our variables of interest are only available on an annual basis, this study uses unified adoption timing, which may prove to be one of the study's limitations.

Another vital variable in this study is *Fintech*. To put it simply, Fintech can be said as the integration between technology and financial activities. Over the last few decades, Fintech innovation has affected many dimensions of financial services, including payments, credits, remittances, savings, insurances and investment management (Sahay, et al., 2020). Consequently, it has grown in popularity since it makes credit more accessible, reduces transaction costs and eliminates information asymmetry (Appiah-Otoo & Song, 2021). Certain studies employ the digital financial inclusion index, mobile payments, and digital loans as the proxy measures for Fintech (Riley, 2018; Bharadwaj, Jack, & Suri, 2019; Appiah-Otoo & Song, 2021). Nonetheless, due to the scarcity of Fintech data in Indonesia, this paper follows Ayse et al. (2020), Asongu & Odhiambo (2019), and Asongu, Nwachuckwu, & Orim (2018) in defining Fintech as the use of mobile phones and the internet for financial transactions (including payments, e-banking and searching for products/services).

To understand the channel through which Fintech might affect poverty, the share of people who have saving accounts (*saving*) and credits (*credit*) is also explored as a proxy for financial inclusion in each district/city. Moreover, employment in service industries (measured by variables *tradefoods_emp*, *transcom_emp*, *finance_emp* and *other_emp*) are taken into account to identify whether adopting the 4G network would affect poverty through the labour market channel.

4.2.3 Control Variables

Our control variables include the working-age population, the share of the population living in rural areas and the proportion of people receiving government assistance in each district/city. In addition, literacy rates and the disparity in access to electricity, good sanitation and safe water are also considered.

The variables mentioned above are included in the model to account for district-specific time-varying characteristics affecting poverty rates.

4.3 Data Overview

The following table provides summary statistics for the variables used in the paper. The dataset contains 1.795 observations drawn from 264 treatment and 95 control districts/cities over five years. Over time, the treatment group has an average poverty rate of 12.45%, which is substantially lower than the control group, with an average poverty rate of 18.58%. Meanwhile, the mean share of people utilizing Fintech is higher in the treatment group (3.69%) compared to the control group (2.04%), although the variation is more prominent in the treatment group.

According to Table 2, on average, districts/cities that adopt the 4G network perform better in every dimension, except the proportion of residents who receive government assistance (treatment: 45.34%, control: 48.71%). This preliminary finding implies that districts/cities that receive more government assistance are, in many ways, less fortunate than other cities, consisting of underdeveloped districts.

Table 2. Summary Statistics

Variable name	Obs	Mean	Std. Dev	Obs	Mean	Std. Dev
	Treatment = 0			*Treatment = 1*		
poverty rate	475	18.584	10.719	1320	12.446	6.195
fintech	475	2.038	1.944	1320	3.685	2.926
credit	475	16.624	11.665	1320	21.694	11.006
saving	475	32.222	14.904	1320	34.944	14.327
tradefoods_emp	475	10.420	5.038	1320	16.696	6.025
transcom_emp	475	2.483	1.659	1320	3.803	2.393
finance_emp	475	0.364	0.420	1320	0.670	0.646
other_emp	475	7.869	8.607	1320	9.192	7.782
working-age pop	475	61.239	13.158	1320	58.832	10.674
rural pop	475	83.570	13.192	1320	71.000	20.448
pov_alleviation	475	48.705	20.704	1320	45.337	18.980
literacy rate	475	91.692	12.948	1320	95.654	4.759
access to electricity	475	81.279	22.541	1320	96.497	6.933
access to safe water	475	53.322	20.984	1320	63.250	17.349
access to good sanitation	475	59.510	19.293	1320	71.149	15.879

5. Results and Discussions

5.1 The Arrival of the 4G Network and the Poverty Rate

Before performing DiD estimations, preliminary regressions are conducted for poverty rate and 4G network adoption. Table 3 shows the simple difference estimates for the poverty rate before and after adoption.

Table 3. Simple Difference Regressions

Dependent Variable *(poverty rate)*	(1) *Pooled OLS*	(2) *FE*	(3) *FE - year effects*
4GNet	**-1.886***** **(0.720)**	**-1.032***** **(0.052)**	**-1.246***** **(0.231)**
district-specific controls	yes	no	yes
year-effect	no	no	yes
fixed-effect	no	yes	yes
Observations	1,795	1,795	1,795
R-squared	0.569	0.408	0.488
Number of districts/cities	359	359	359

Notes: The table reports the estimation from three simple differences regressions (Pooled OLS, FE and FE - year effects). District-specific controls included are working-age population rate, literacy rate, % population who receive subsidies, % population living in rural areas, access to electricity, good sanitation and safe water. Standard errors in parentheses are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1

The pooled OLS and fixed effect estimations (columns 1 and 2) indicate that adopting the 4G network reduces poverty by approximately 1.032–1.886 ppts, and the effect is statistically significant at a 1% significance level. After adjusting for year effects, the estimated coefficient changes to -1.246, indicating that the poverty rate may also be affected by time trends caused by business cycles/shocks or other unobserved factors.

The negative relations between poverty and 4G network adoption align with the prediction that even access to stable and faster internet connections will increase the number of people utilizing the internet for financial transactions, increasing economic activities and reducing poverty. However, relying solely on the above estimates is not appropriate, as selection bias might exist due to differences in embedded characteristics between the districts covered by the 4G network and those that are not. Therefore, DiD regression is employed to identify the effect of 4G network adoption on poverty rates between the two groups.

The first finding from the DiD regressions is summarized in Table 4: 4G networks adoption estimated effect on poverty rates in Indonesia. Panel A shows the results of the two-period DiD. As shown in Panel A column (1), the DiD estimate is negative and significant, suggesting that the adoption of 4G networks leads to a 0.208 ppts reduction in poverty rates for districts/cities in the treatment group relative to the control group. When district-specific time-varying controls, year effect and region-year effect are included, leaving out the big cities, the effect increases to 0.235 ppts (column 4).

Table 4 – The 4G network adoption effect on poverty rate (DiD Regressions)

Dependent Variable *(poverty rate)*	(1) *poverty_rate*	(2) *poverty_rate*	(3) *poverty_rate*	(4) *poverty_rate*
		A. Two - periods DiD		
post*4GNet	**-0.208***	**-0.316****	**-0.310****	**-0.235***
	(0.113)	**(0.123)**	**(0.123)**	**(0.136)**
district-specific controls	no	yes	yes	yes
year-effect	no	no	yes	yes
fixed-effect	yes	yes	yes	yes
region-year effect	no	no	no	yes
Observations	718	718	678	678
R-squared	0.435	0.450	0.459	0.511
Districts/cities	districts and cities	districts and cities	district only	district only
Number of districts/cities	359	359	339	339
		B. Generalized DiD		
post*4GNet	**-0.297****	**-0.414*****	**-0.341*****	**-0.231***
	(0.119)	**(0.119)**	**(0.118)**	**(0.137)**
district-specific controls	no	yes	yes	yes
year-effect	no	no	yes	yes
fixed-effect	yes	yes	yes	yes
region-year effect	no	no	no	yes
Observations	1,795	1,795	1,695	1,695
R-squared	0.415	0.454	0.507	0.554
Districts/cities	districts and cities	districts and cities	district only	district only
Number of districts/cities	359	359	339	339

Notes: The generalized DiD in the table refers to the DiD setting with multiple pre-and post- periods. District-specific controls included in regressions are working-age population, literacy rate, % population living in rural areas, access to electricity, good sanitation and safe water. Additionally, region-year is included in the regression to control time-varying trends caused by the districts/cities' geographical locations. Seven districts are excluded from the observations due to the incomplete data. The standard errors in parentheses are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1

Previously, Figure 1 and Table 1 demonstrate that both groups experienced a downward trend in poverty rates over the observation periods. Nonetheless, the DiD estimate shows that while both groups experienced a decline in poverty, the treatment group experienced a more significant decline. The treatment group likely has more people benefit from stable and faster internet connections, improving their chances to access information and job opportunities, decreasing transaction costs, thereby improving household income and alleviating poverty.

To further control the effect of time trends and ensure the control group is an excellent counterfactual comparison for the treatment group, the generalized DiD with multiple pre-and post-treatment periods are estimated (Angrist & Pischke, 2008). Table 4 Panel B shows the estimation results from equations (2) and (3). Panel B columns (1) and (2) show that the coefficient estimates are consistent with the two-period DiD; the effects are becoming more prominent (0.297 ppts and 0.414 ppts) and significant. After controlling for the year and region-year effect (columns (3) and (4)), the impact decreased to 0.341 ppts and 0.231 ppts, respectively; nevertheless, it remains significant, confirming the consistency of our estimates.

One might also be concerned about the effect of government transfers on poverty. Since the transfer programs began in 2007, the number of beneficiaries has increased, providing poor people with additional sources of income, increasing their opportunity to have productive investment, thus reducing poverty levels. However, Table 5 columns (1) and (2) show that the DiD estimates do not change much when the percentage of people who receive poverty alleviation programs is considered. These findings imply that the effects possibly not be significant as we excluded all large cities/districts.

Moreover, the government expanded the program's recipients while gradually distributing non-cash assistance since 2016 via *e-Warong Kube – PKH,*[11] to boost the program's effectiveness and promote an inclusive national financial system (Mawardi, et al., 2017). The first pilot project was conducted in five districts/cities: Batam, Balikpapan, Denpasar, Kediri and Malang. By the end of 2016, the government successfully opened 108 *e-Warong* units in 35 districts/cities. As the government gradually uses Fintech (e.g. *e-Warong*, mobile money, QR codes and e-money) for social programs, many poor households become aware of transaction accounts' salience, motivating them to open formal accounts. Therefore, controlling the number of people receiving the programs might eliminate the channel through which 4G network adoption can affect poverty in Indonesia, a case of lousy control (Angrist & Pischke, 2008).

Table 5. The 4G network and poverty rate, controlling for poverty alleviation

Dependent Variable *(poverty rate)*	(1) *Equation (3)*	(2) *Controlling for pov_alleviation*
Post*4GNet	**-0.231***	**-0.230***
	(0.137)	**(0.137)**
district-specific controls	yes	yes
year-effect	yes	yes
fixed-effect	yes	yes
region-year effect	yes	yes
Observations	1,695	1,695
R-squared	0.554	0.554
Districts/cities	district only	district only
Number of districts	339	339

Notes: The Baseline regression is based on Equation (3), i.e. similar to Table 4 Panel B Column 4. The standard errors in parentheses are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1

[11] *e-Warong Kube – PKH* is an agent bank or outlets (shops) that works with the appointed banks and designated as a withdrawal location for government social transfers. *e-Warong* can perform the function of opening a new account, cash deposit/withdrawal, purchase and bills payments.

5.2 *Mediating Effect Through an Increase in Fintech*

Fintech is closely related to the adoption of 4G networks in Indonesia. The arrival of stable and faster internet connection through the 4G network adoption generates waves of technological innovation across the country, which can be seen in an increase of the people who use the internet and mobile phone (Appendix 1).

According to "*e-Conomy SEA 2019*[12]*"*, Indonesia's digital economy has become the most prominent and fastest-growing sector in the region, supported by considerable increases in internet users since 2015 and the rise of *Gojek* and *Grab* (Jurriens & Tapsell, 2017; Oxford Business Group, 2020). Indonesia now has more than 150 Fintech startups, a 78% increase over 2015. As of 2019, Indonesia had 249 Fintech companies, and the number is expected to continue growing in the coming years.[13] Table 6 below shows the results of Equation (3) for Fintech, credit and saving.

Table 6. The 4G network adoption effect on Fintech, credit and saving

Variables	(1) *fintech*	(2) *fintech*	(3) *credit*	(4) *credit*	(5) *saving*	(6) *saving*
post*4GNet	**1.398*** (0.202)**	**0.680*** (0.195)**	**3.085*** (0.626)**	**1.437** (0.637)**	**0.124 (0.993)**	**-1.281 (1.052)**
district-specific controls	no	yes	no	yes	no	yes
year-effect	yes	yes	yes	yes	yes	yes
fixed-effect	yes	yes	yes	yes	yes	yes
region-year effect	no	yes	no	yes	no	yes
Observations	1,695	1,695	1,695	1,695	1,695	1,695
R-squared	0.695	0.765	0.658	0.695	0.630	0.673
Number of districts	339	339	339	339	339	339

Notes: The table reports the estimation from DiD regressions with Fintech, credit and saving as dependent variables. District-specific controls included are working-age population, literacy rate, % population living in rural areas, and access to electricity. Additionally, region-year is included in the regression to control time-varying trends caused by the districts/cities' geographical locations. Standard errors in parentheses are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1

The DiD coefficient estimates in columns (1) and (2) are significant at a 1% significance level, inferring that 4G network adoption increased the number of people using Fintech in the treatment districts by approximately 1.398 ppts relative to the control districts. The effect decreases to 0.680 ppts after controlling for time-varying district characteristics and regional trends. These results are economically significant, given the internet users have only increased from 21.98% to 47.69% in the last five years (BPS-Statistics Indonesia, 2019). As shown in columns (3) and (4), significant results are also found for credit access, with coefficient estimates of 3.085 and 1.437, respectively. Surprisingly, column (6) shows that the proportion of people with saving accounts

[12] Join report published by Google, Temasek and Bain.
[13] Retrieved from https://www.cekindo.com/blog/fintech-indonesia on August 2021.

decreased by approximately 1.281 ppts in treatment districts compared to control districts.

Two possible reasons might explain these findings. First, Fintech provides individuals with mobile money (i.e., *OVO*, *GoPay* and others) that can be used for certain transactions. People, particularly millennials, prefer to store their money in their mobile accounts rather than conventional banks since payments are more convenient. Second, the surprising result is due to measurement inconsistency. In *Susenas* 2017, respondents were asked, *"How many people in their household have saving accounts in formal financial institutions?"*. In contrast, they were asked about *"whether an individual in their household has saving accounts in formal financial institutions"* in other years. These minor alterations in survey questions caused inconsistencies in respondents' answers.

However, account ownership increased by more than 20 ppts in 2018 compared to 2016, according to Indonesia Financial Inclusion Insights Tracker Surveys (2019). Moreover, it has nearly doubled in rural areas due to Fintech and government assistance programs (Figure 3 below). As a result, it is highly likely that data inconsistencies contributed to inconsistent findings.

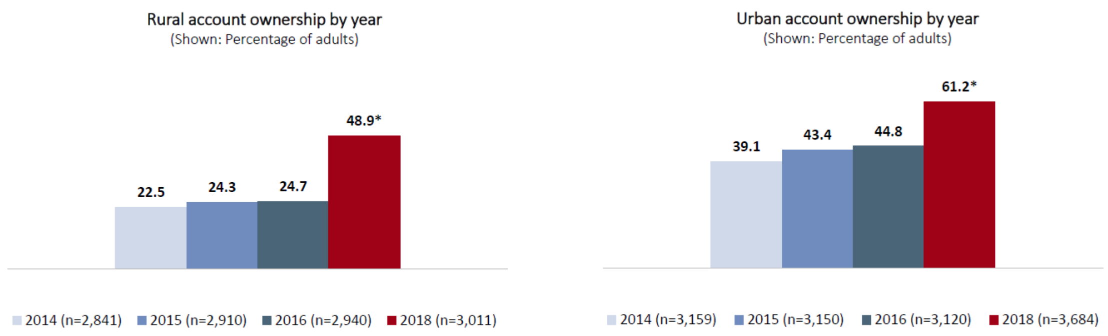

Figure 3. Urban/rural account ownerships by year

(Source: Indonesia Financial Inclusion Insights Tracker Surveys, retrieved from Financial Inclusion Insight Indonesia 2018)

While we cannot make conclusive inferences that the arrival of 4G network increases people's access to savings accounts, the former undoubtedly increases their use of Fintech, which implies increases their access to credits, as Fintech in Indonesia is still dominated by peer-to-peer lendings and payments (Indonesia Financial Services Authority, 2021). The findings fortify the argument that the arrival of the 4G network has a mediated effect on poverty via Fintech and credit access. If our hypothesis is correct, removing Fintech effects on poverty would reduce the DiD estimated coefficient on the poverty rate, making it insignificant in some cases. Table 7 shows the DiD estimates on poverty rate after Fintech effects are eliminated via a two-stage regression. Details on the 1st stage regressions applied can be seen in Appendix 2.

As shown in Table 7 Column (3), removing Fintech effects on poverty reduces the DiD estimated coefficient to -0.192 from -0.231, and it becomes statistically no different than zero, corroborating the previous findings. However, the coefficient estimate is pretty similar to Column (4), where the *Gojek* effects on the poverty rate are eliminated in the 1st stage regression. These similarities indicate the possibilities that Fintech might capture the effect of *Gojek* waves. In other words, it might be the case that a stable and faster internet connection creates internet-based job opportunities (e-commerce), increasing employments and incomes, thus reducing poverty in Indonesia.

Table 7. The 4G network and poverty rate, eliminating Fintech effects

Dependent Variable *(poverty rate)*	(1) *Eq - (2)*	(2) *Eq - (3)*	(3) *No Fintech effect*	(4) *No Gojek effect*
post*4GNet	**-0.341***** **(0.118)**	**-0.231*** **(0.137)**	**-0.192** **(0.135)**	**-0.203** **(0.137)**
Observations	1,695	1,695	1,695	1,695
R-squared	0.507	0.554	0.005	0.095
Number of districts	339	339	339	339

Notes: Fintech effects are eliminated in two steps. In the 1st stage, we estimate the effect of Fintech on poverty rates, and then we use the residuals from 1st stage regression in the DiD regressions. Additionally, we also include the result from regression after eliminating the effects of *Gojek* services. The standard errors in parentheses are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1

5.3 The Growth of Mobile App Services and Employments

Gojek, as one of the most popular app-based transport services in Indonesia, gained widespread recognition in 2015. Since its inception in 2010, with only 20 motorcycle taxis in Jakarta, *Gojek* has expanded beyond taxis. Following *Gojek* apps' launch in 2015, they expanded their services beyond the capital, offering motorcycle taxi services, food delivery, ticket bookings, massage services and courier services. Orders ramped up dramatically to 300,000 per day in 2016, and *Gojek* became Indonesia's first unicorn, raising $550 million in new capital (Digital News Asia, 2016). By the end of 2018, the services had covered 167 districts/cities in Indonesia (Gojek, 2018).

Despite the polarizing effect of app-based transport and service providers, consumers have not only embraced the convenience and economy of app-based services but have also demonstrated their willingness to defend *Gojek*, *Uber and Grab's*[14] significance for their lives. Moreover, it has undoubtedly profited the self-employed conventional drivers who joined the app-based platform through increasing demand, higher incomes and additional benefits such as insurance (Ford & Honan, 2017). Due to the lack of *Gojek* data, the share of people working in the services industry during the observation periods is examined to substantiate our findings.

The DiD regression based on Equation (3) is applied to the share of people working in four different services categories: (i) trade, hotel, food and restaurants; (ii) transport, communication and IT services; (iii) financial and insurance services, and (iv) other

[14] *Gojek, Uber and Grab* are three biggest player in app-based transport services in Indonesia.

services. The following table shows the DiD estimates for the proportion of people employed in each service category, according to *Susenas* 2015–2019.[15]

Table 8. The 4G network and people working in service sectors

Variables	(1) *tradefood_emp*	(2) *transcom_emp*	(3) *finance_emp*	(4) *other_emp*
post*4GNet	**0.998*** (0.308)**	**0.105 (0.123)**	**0.089** (0.044)**	**0.425 (0.596)**
Observations	1,695	1,695	1,695	1,695
R-squared	0.361	0.075	0.087	0.817
Number of districts	339	339	339	339

Notes: The table shows the DiD regressions for people working in trades, hotels, foods and restaurants *(tradefood_emp)*, transportation, communication and IT *(transcom_emp)*, finance and insurance *(finance_emp)* and other services *(other_emp)*, based on Equation (3). Due to a lack of data resources, employment data are constructed from *Susenas*. The standard errors in parentheses are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1

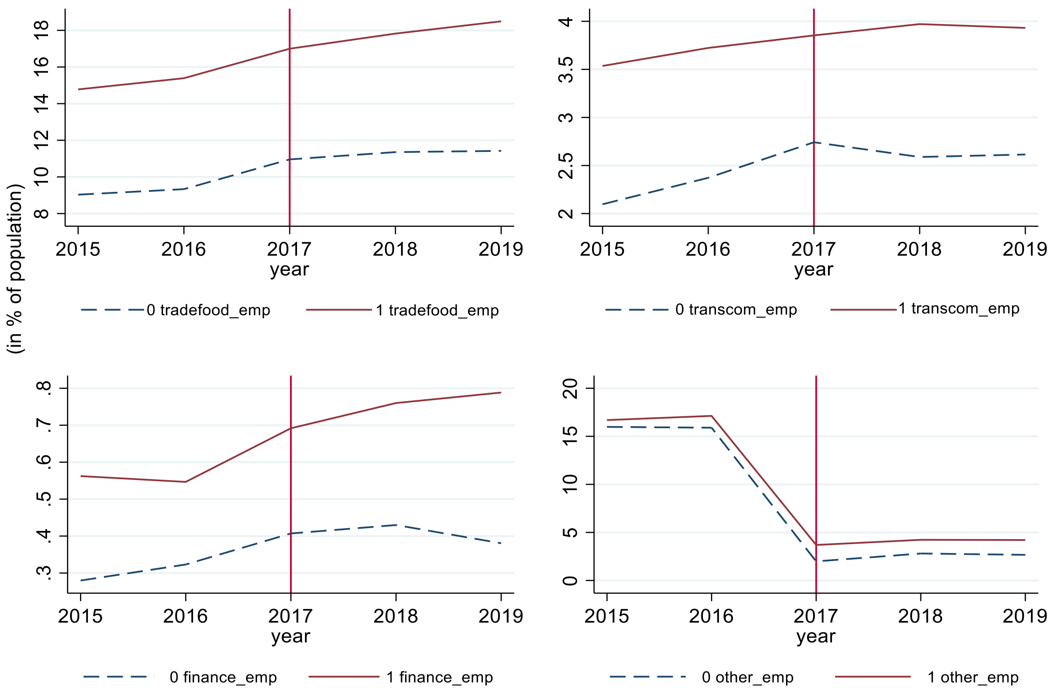

Figure 4. Trends in employment in four categories of service, for treatment and control districts

It can be observed in Table 8 that all coefficient estimates indicate an increase in employment, with the most significant increase of 0.998 ppts in trades (retails and wholesales), hotels, foods and restaurants for treatment districts compared to control districts. Another substantial increase of 0.089 ppts is observed in the financial and

[15] Indonesia has more detailed labour survey, called National Labour Force Survey *(Sakernas)*. However, we decide to base our analysis with *Susenas* to maintain our consistency.

insurance sectors. Surprisingly, an insignificant increase in transport, communication and IT is found. However, as illustrated in Figure 4 and the confidence interval in Appendix 3, adopting 4G networks could increase transport, communication and IT employment by up to 0.348 ppts, which is an economically significant increase given the sector's average employment growth of 22.78% by the end of 2018 (Sakernas, retrieved from World Bank, 2019).

Finally, it is concluded that adopting 4G networks would increase Fintech usage, increasing credit access, thus reducing poverty in Indonesia. Additionally, Fintech could generate employment opportunities for rural residents, increasing their incomes and alleviating poverty. The findings are consistent with evidence found by Hjort and Poulson (2019) in Africa.

6. Robustness Checks

6.1 Testing the Validity of DiD Regression

The parallel trend assumption is critical to the validity of DiD regression. This study builds on previous research to test the parallel trend assumption with the idea of Granger causality (Angrist & Pischke, 2008; Autor, 2003; de A. Lima & Neto, 2018). The test is applicable for multiple-period DiD regression by adding leads and lags of the treatment in the equation, resulting in:

$$Pov_{dt} = \lambda_t + \theta_d + \sum_{\tau=0}^{m} \beta_{\_\tau} D_{d,t-\tau} + \sum_{\tau=1}^{q} \beta_{+\tau} D_{d,t+\tau} + \boldsymbol{\gamma_i X'_{idt}} + \varepsilon_{idt}, \quad (6)$$

where Pov_{dt} is poverty rate for district d at year t, and λ_t and θ_d are district and year fixed effects, respectively. $D_{d,t-\tau/t+\tau}$ represents the interaction between treatment variable and year dummies. Consequently, pre-treatment trends and the varying effects of the treatment can be observed.

Table 9 summarizes the results of Equation (6). The estimated coefficient one year prior to treatment is statistically not different from zero, indicating the absence of an anticipatory effect; thus, the parallel trends assumption holds. As a result of the findings, it can be concluded that both the treatment and control groups' poverty rates would have followed a similar trend in absences of the treatment, such that the control group serves as an excellent counterfactual for the treatment group. Furthermore, as illustrated in Figure 5, the estimated coefficient becomes significant and negative one year after the adoption, and the impact continues to grow in the subsequent year. This indicates that the adoption of 4G networks has a beneficial effect on poverty reduction in the treatment districts.

Table 9. Parallel Trend Assumption Test Results

Variables	*Regressors*			
	1-year prior	***adoption year***	***1-year after***	***2-years after***
Dependent variable: poverty rate	**-0.067**	**0.096**	**-0.317****	**-0.334****
	(0.077)	**(0.103)**	**(0.149)**	**(0.169)**
district-specific controls	yes			
year-effect	yes			
fixed effect	yes			

Notes: The table shows Equation (4) results, which allows for effects before, during and after the treatment. Because of the series limitation, we can only estimate the year before the treatment, treatment year, one year after and two years after the treatment. The standard errors in parentheses are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1

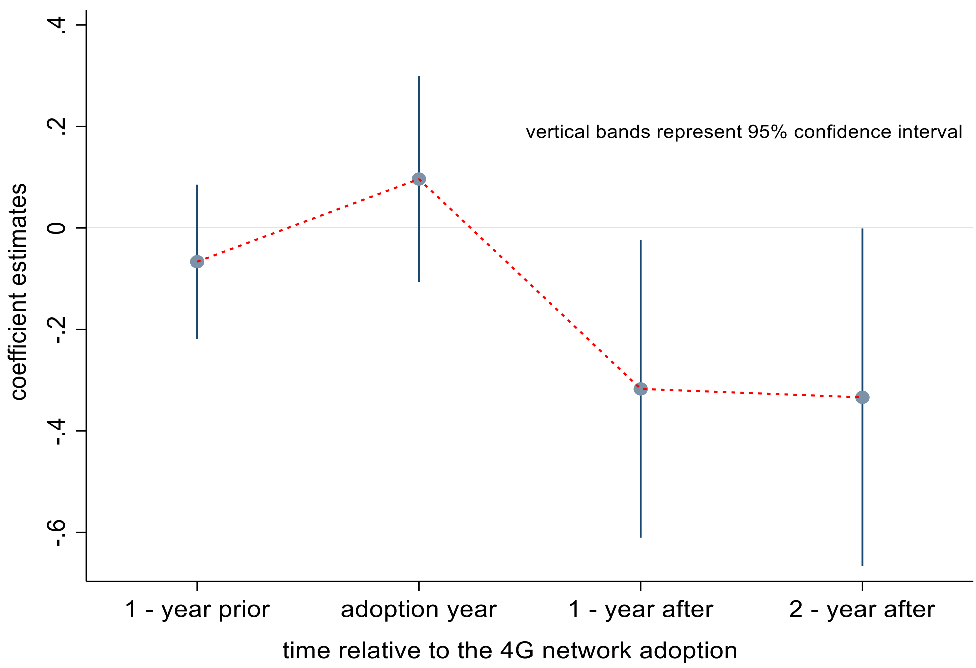

Figure 5. Coefficients plot from the parallel assumption test results on Table 9

6.2 Estimating the 4G Network's Impact for Different Sample Groups

The heterogeneous effect of 4G network adoption across the poverty percentile is first examined. If adopting the 4G network is beneficial for poverty reduction and assuming the timing of coverage is exogenous, the impact should be more significant in districts with higher poverty rates prior to the adoption year. According to Table 10 Panel A, the impact of 4G network adoption is higher in the upper 25% districts. The treatment districts would have an additional 0.694 ppts decrease in poverty rate compared to the control districts. The impact is less pronounced in other percentiles; however, it still contributes positively to poverty reduction. Low poverty districts usually have better access to financial services prior to the treatment; therefore, the marginal impact of 4G networks and Fintech for poor people in those districts is a lot smaller.

Table 10. The 4G network adoption and poverty rate, varying the sample

Dependent Variable	(1)	(2)	(3)
		poverty rate	
(poverty rate)	*upper 25*	*pct 50*	*lower 25*
Panel A. Estimation for different percentiles of poverty distribution			
post*4GNet	**-0.694****	**-0.166**	**-0.088**
	(0.322)	**(0.175)**	**(0.113)**
Panel B. Excluding upper and lower 10% districts based on internet usage			
post*4GNet		**-0.269***	
		(0.139)	

Notes: Panel A displays Equation (3) regression results for different sample groups based on the distribution of poverty rates. In Panel B, districts with upper and lower 10% of internet usages are excluded from the sample. All regressions include district-specific controls, year effect, fixed effect and region-year effect. Standard errors in parentheses are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1

In Table 10 Panel B, the upper and lower 10% of districts based on internet usage are excluded from the sample. Previously, the treatment districts are selected based on the minimum areas covered by the 4G network in 2017. Even though cities are already excluded from the sample, large districts are likely to have stable and faster internet connections prior to the arrival of the 4G network, assuming they have better infrastructures and networks. Meanwhile, it is also advisable to not include inaccessible rural districts in control groups, as they are very likely to differ from the treatment groups (Hjort & Poulsen, 2019). If that is true, we might incorrectly attribute an estimated effect to 4G network adoption. Nonetheless, after excluding the smallest and largest districts from the sample, the results are essentially unchanged – if anything, the estimate grows in magnitude from -0.231 to -0.269.

6.3 Estimation Using Different Grouping Methods

Along with sample changes, different grouping standards are used to evaluate the robustness of estimated coefficients. Three different grouping methods are used in the tests. First, the treatment and control groups are separated using self-reported village-level data from the 2018 Village Potential Survey *(Podes 2018).* Second, it was argued earlier that 4G network adoption affected poverty by increasing the number of people using mobile phones and the internet for financial transactions (Fintech). Thus, dividing the treatment and control groups according to the number of mobile phone users in each district should be reasonable (treatment: higher than or equal to 50% and control: lower than 50% population). Third, previously the treatment group is defined as the districts that have at least 50% of their land areas covered by the 4G network. Thus, modifying the threshold to 75% of land areas covered could be used to test the robustness.

As shown in Table 11 columns (1), (2) and (3), changing the grouping methods had little effect on the estimated coefficients. Compared to the control group, the treatment group experiences a poverty reduction of approximately 0.218 ppts, 0.247 ppts and 0.321 for *Podes* 2018, mobile phone usage and 75% covered land areas, respectively, and the effects are becoming more substantial. These results demonstrate the consistency of our DiD estimation under the former grouping method from the Ministry of Communication and Information Technology.

Table 11. The 4G network adoption and poverty rate, different grouping methods

Dependent Variable *(poverty rate)*	(1) *Podes 2018*	(2) *Mobile Phone Usage*	(3) *75% Covered*
post*4G_podes2018	**-0.218***		
	(0.113)		
post*4G_mphone		**-0.247***	
		(0.126)	
post*4G_75%			**-0.321*****
			(0.115)
district-specific controls	yes	yes	yes
year-effect	yes	yes	yes
fixed-effect	yes	yes	yes
region-year effect	yes	yes	yes

Notes: This table reports the regression results from Equation (3) using self-reporting 4G networks coverage based on Village Potential Survey 2018 (*Podes* 2018), mobile phone usage and 75% covered land areas as grouping standards. Standard errors in parentheses are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1

6.4 Using Placebo Treatment on the DiD Regression

In addition, a placebo treatment capturing the districts that will be covered by the 4G network in the following year is employed as a falsification test in the DiD regression. As a result, the DiD coefficient in Table 12 Column (2) becomes statistically insignificant, approaching zero. The test verifies that the arrival of 4G networks reduces poverty rates in Indonesia.

Table 12. The 4G network adoption and poverty rate, using placebo treatment

Dependent Variable *(poverty rate)*	(1) Equation (3)	(2) *Using placebo treatment*
post*4GNet	**-0.231***	**0.047**
	(0.137)	**(0.170)**
district-specific controls	yes	yes
year-effect	yes	yes
fixed-effect	yes	yes
region-year effect	yes	yes
Observations	1,695	1,695
R-squared	0.554	0.550
Number of districts	339	339

Notes: This table shows the regression results from Equation (3) when placebo treatment is used. The placebo treatment is constructed from the districts that will cover 50% of their land areas with the 4G network in the upcoming year. The standard errors in parentheses are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1

6.5 Ignoring the Time-Series Information

Bertrand, Duflo & Mullainathan (2004) demonstrate in their paper that serial correlation might bias standard errors in DiD analysis. They propose a simple method to account for the problem by ignoring the time-series information when computing standard errors. Following their method, the pre-post treatment period of 2015–2017 and 2018–2019 are considered. Table 13 shows the DiD regression results after removing the time-series information.

Table 13. The 4G network adoption and poverty rate, ignoring time-series information

Dependent Variable *(poverty rate)*	(1) *Ignoring time-series information*
post*4GNet	**-0.343***** **(0.128)**
fixed-effect	yes
Observations	678
Number of districts	339
R-squared	0.555

Notes: This table reports the DD regression results, ignoring time-series information. This test treats the panel as two periods, pre-and post-treatment. The standard errors in parentheses are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1

Column (1) indicates that the estimated coefficient remains negative and statistically significant, consistent with the findings in Table 4, demonstrating that the time-trend does not affect the impact of 4G network adoption on poverty reduction in Indonesia. The test results conclude that the estimated effect of 4G network adoption on poverty rates in Indonesia is robust and likely to be a causal response.

7. Conclusion

This study examines the impact of the arrival of 4G networks on poverty rates in Indonesia. To do so, the variation in the timing of 4G network adoption in 514 districts/cities is exploited. Simple difference regressions demonstrate that, on average, the adoption of 4G networks have a negative association with poverty. Then, using the DiD approach, the above results are confirmed. The arrival of 4G networks has a more significant impact on poverty reduction in districts where more than 50% of their land areas are covered by the 4G network, controlling for districts, region and year effects. Thorough probing of our generalized DiD approach's identifying assumptions suggests that the estimates reflect causal responses of access to 4G networks on poverty rates. Additionally, it is demonstrated how 4G network adoption may impact poverty by increasing Fintech usage, improving access to credits (i.e., financial inclusion), thereby reducing poverty in the region. Moreover, Fintech might capitalize on the waves of mobile app-based services (i.e., *Gojek*, *Uber* and *Grab*), generating internet-based job opportunities (e-commerce), increasing employment and reducing poverty.

This study's challenge lies in the possibility of unprecise timing of 4G network adoption in each district, as the available datasets are on an annual basis. Additionally, the timing of adoption may not be completely random as the providers determine it. The district- and time-fixed effects, time-varying district covariates and regional trends are added to the model to lessen the bias caused by the selection issue. Furthermore, a parallel trend test conditional on controls is performed to confirm the validity of our identification strategy.

The study's limitations motivate further research to better understand the impact of stable and faster internet connections on poverty. Firm-level data or a more comprehensive labour survey dataset could be utilized to elucidate the interrelationship between Fintech, employment and poverty. Additionally, a more consistent dataset is required to quantify financial inclusions for a more conclusive analysis. Finally, because this study only examined the short-run impact of the arrival of 4G networks on poverty, it may be beneficial to conduct additional research on the long-run impact of such technological shocks on poverty.

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