Does the Mobile Phone Affect Social Development? Evidence from Indonesian Villages[*]

Jahen F. Rezki[†]

January 25, 2023

Abstract

This paper analyses the impact of Information and Communication Technology (ICT) on social development in Indonesian Villages. In this study, I use data from different waves of the Indonesian Village Potential Statistics (*Potensi Desa*) to determine whether mobile phone signal strength affects social development indicators. The results indicate that villages with a strong signal are statistically more likely to possess the proper infrastructure programs. Furthermore, mobile phones increase the availability of village libraries and access to credit for small and medium enterprises (SMEs). Using the plausibly exogenous variation of lightning strike intensity as the instrumental variable, this study suggests that higher mobile phone signal strength is positively associated with the policies implemented by the village head and leads to better social development. As the mechanisms, this study shows that mobile phones increase the likelihood of having collective action and civic engagement, increasing villagers' political participation and use of telecommunication services, thus leading to an increase in village government's accountability.

Keywords: Mobile Phone, ICT, Village Government, Indonesia, Accountability, Policy-making

JEL Classification: D73, D78, H4, H7, L96, O1

---

[*]I thank the editor Erik Bohlin and anonymous referees for useful comments and suggestions. I am deeply grateful to Giacomo De Luca and Andrew Pickering for their support. I would also like to thank Thomas Cornelissen, Thilo Huning, Julien Labonne and Anirban Mitra, Michael Shallcross for their helpful comments and supports. I am thankful to the attendees of CSAE Conference 2018, Nordic Conference on Development Economics 2018 and RES PhD Meeting 2018 for their feedback. I would also like to acknowledge BPS Statistics Indonesia, LPEM-FEB UI, The IPUMS-International Team and NASA Global Hydrology Resource Centre (GHRC) DAAC for providing the data for this research. I also thank Mervin Goklas Hamonangan for excellent research assistance. Thanks to Indonesia Endowment Fund for Education (LPDP-RI) for their financial support (Grant number: 0044455/EK/D/2/lpdp2014). This paper supersedes an earlier working paper under the title "Call Your Leader: Does the Mobile Phone Affect Policymaking?". All errors are my own.

[†]Department of Economics, Universitas Indonesia, Indonesia and LPEM-FEB UI, Indonesia. Email jahen.fr@ui.ac.id.

1 Introduction

The role of new media and the rapid growth of information and communication technology (ICT) have become increasingly significant over recent years. The development of ICT has been documented by Aker and Mbiti (2010), who explain the growth of mobile phone adoption and its impacts on Africa's economic development. The World Bank (2016) describes the extensive growth of ICT throughout developing countries. Nonetheless, studies on the impact of ICT in policy-making are limited. The majority of previous studies focus their research on the impact of mass media (e.g. television, radio, newspaper) and information on voter turnout or political accountability (Cook et al., 1983; Persson and Tabellini, 2000; Besley and Burgess, 2002; Strömberg, 2004b; Olken, 2009; Snyder Jr and Strömberg, 2010; Gentzkow et al., 2011; Enikolopov et al., 2011; Aker et al., 2017).[1] To my knowledge, studies on the impact of ICT, especially mobile phones, on policy-making are scarce.

Despite many studies have observed the positive impact of ICT on several outcome indicators, other studies have suggested the adverse effect of ICT, for instance on conflict. A seminal study by Yanagizawa-Drott (2014) estimated the impact of communication through radio propaganda on violence and mass killings in Rwanda. The study suggests that access to information boosts the number of violence during the dark period of Rwanda conflict. A similar study in Indonesia has shown a similar result, where areas with a better communication infrastructure tend to have a higher probability of local conflict (Yudhistira et al., 2021). Moreover, Marler (2018) suggests that mobile phones may also play a pivotal role in fuelling higher inequality, even though it may vary across countries.

Indonesia is an ideal natural laboratory for this study because not only had the country recently democratised and become more decentralised after being led by President Suharto for 32 years, but also because ICTs (especially mobile phones) have been growing in use at an increasing rate (Rohman and Bohlin, 2014). In 2002, only 11.7 million people owned mobile phones, while in 2016 almost 385.5 million people owned mobile phones. Moreover, Law No. 36/1999 on telecommunication promoted the liberalisation of ICT sectors in Indonesia, which led to an increase in the number of telecommunication providers. Consequently, the cost to use and connect to a mobile network decreased significantly (Lee and Findlay, 2005).

In terms of political context, the introduction of Law No. 22/1999 on regional administrations,

[1]Several studies have investigated the role of mobile phones in developing countries, such as: Aker et al. (2017) on the role of mobile phones and newspapers in voting intention in Mozambique, Jensen (2007) on the effect of mobile phones in the fisheries sector in South India, Aker (2010) on the impact of mobile phones on agriculture markets in Niger and Bailard (2009) on the relationship between mobile phone diffusion and corruption in Namibia.

followed by Law No. 6/2014 on village administrations, increased the power of local administrative, as well as village governments.[2] These laws were introduced to ensure village governance and to improve community participation at the village level. Indonesia has a substantial number of villages. In 2014, there were around 82,190 villages across the country. Moreover, there has been an increase in local government responsibility, according to Martinez-Bravo (2014) and Martinez-Bravo (2017) who examined the role of local leaders in Indonesia after the country's democratisation. These studies suggest that local leaders play a significant role in implementing policy.

To discuss the role of mobile phone usage on social development[3], I use different waves of data from the village census (*Podes*), i.e. data from 2008, 2011 and 2014. The dataset used in this study consists of 163,806 observations, which are collected from 54,602 villages across 33 provinces, 456 districts and 6,292 sub-districts. *Podes* provides extensive information about the village characteristics; it has data related to village-level administrations, village economic activities, village geographical conditions, etc. The data also provides information about the ICT development in the village (e.g. signal strength, number of households with fixed-line subscription, number of internet cafes, number of public phones, etc.) Therefore, it becomes possible to investigate the role of mobile phone usage in policy-making and collective action at the village level in Indonesia. I use a binary variable to represent signal strength coverage at the village level as my main explanatory variable. In this study, I focus on the impact of mobile phones via text messages and/or phone calls. I employ a linear probability model and a probit model to estimate the impact of signal strength on policies.

A potential problem with using signal strength is the possibility that it is non-random, which could bias the estimation results. Areas with better infrastructure and larger populations tend to have better signal strength, because the telecommunication sector invests heavily in these areas. This supported by Buys et al. (2009), who reveal that mobile phone signal depends on the presence of a cell tower, size of the population, cost of maintaining the tower, cost of installing the tower, and the national competition policy. Another potential problem is related to the measurement error of the signal strength variable, which could affect the estimation results.

To address this concern, I employ an instrumental variable strategy by using the plausibly exogenous variation of flash rate (or lightning strike) intensity at the village level. Greater instances of lightning strike lead to slower connectivity. Given the fact that Indonesia is located in a tropical

[2] A study by Rezki (2022) suggests that after the Suharto's regime, the degree of political competition at the district level in Indonesia has increased and influenced local economic performance.

[3] In this study I use the term social development and policymaking interchangeably. Social development in this study is specific to policies that will be beneficial for the wellbeing of the society, for example: building more infrastructure, providing trainings, granting financial access to do economic activities

area, and that there is significant geographical variation within the country, I expect flash rate incidences to affect signal strength quality. Using data from the National Aeronautics and Space Administration (NASA), I show that areas with higher lightning strike incidence have lower signal strength.

This paper finds that higher signal strength is associated with an increased presence of village rehabilitation programs. The results are robust for different estimation methods. I also find that stronger signal strength will increase the incidence of village rehabilitation programs where the beneficiaries are poor people. Moreover, the same patterns are observed for the availability of village libraries and access to credit for small and medium enterprises (SMEs). I also find that higher signal strength increases the likelihood of villages possessing libraries by 43 percentage points, and access to credit by 40 percentage points. I do not, however, find any effects on the provision of training to improve villagers' skills.

As the types of villages in Indonesia differ greatly depending on location, urban (*Kelurahan*) or rural (*Desa*), I investigated whether signal strength has heterogeneous effects. Signal strength is estimated to have a stronger influence in rural villages, especially with regard to village rehabilitation programs. However, I am unable to infer any meaningful results for villages in urban areas. One potential explanation is that the different types of village governments are run differently: *desa* in rural areas the village head is elected by the people and in urban areas, the village head is appointed by the district and sub-district governments. Another possibility is that inhabitants of urban areas have alternative sources for collecting information. Therefore, rural villages would benefit more significantly from the introduction of ICTs.

I propose several mechanisms that explain why mobile phones affect policies. First, mobile phone signal coverage affects villagers' ability to initiate and organise civic engagement activities. One channel to improve village conditions is through collective action and therefore access to better mobile phone coverage will increase the likelihood of an improvement in villages' infrastructures. Moreover, better signal strength is associated with better government performance. I show that areas with better signal strength will increase the likelihood of improving village governance and will also reduce the incentives for corruption. The exchange of information and an increase in transparency increase village government accountability. Second, areas with better mobile phone coverage increase the likelihood of individuals' participation in village elections, which is considered a good indicator of better government performance and higher political engagement. Well informed villagers will increase the pressure upon the village head to perform well. The last mechanism is that better mobile phone signal strength will make villagers use mobile phones more frequently and interact more with other villages and with their own village. I show that individuals who are living in areas with better signal strength will have higher telecommunication consumption.

This study contributes to at least four strands of literature. First, it contributes to the important role of ICT and mobile phones in development economics, especially in the context of developing countries (Jensen, 2007; Aker and Mbiti, 2010; Aker, 2010; Aker and Fafchamps, 2014; Aker et al., 2017) by showing that mobile phone use will increase the likelihood of having policies that will improve villages' conditions. The use of village level governments in a country like Indonesia may provide a different perspective about the role of ICT on social development. Second, this study relates to the effects of new media on policies and political accountability (Persson and Tabellini, 2000; Strömberg, 2001; Besley and Burgess, 2002; Strömberg, 2004a,b; Snyder Jr and Strömberg, 2010; Gentzkow, 2006; Gentzkow et al., 2011; Enikolopov et al., 2011; Reinikka and Svensson, 2011; Andersen et al., 2011; Enikolopov and Petrova, 2015) by exploring the role of a non-traditional media, such as mobile phones, which have different characteristics to other media in the case of some policies. The different characteristics of mobile phone will provide an alternative perspective on the role of traditional media on social development. Third, this study explores the role of media and social and political mobilisation (Olken, 2009; Pierskalla and Hollenbach, 2013; Shapiro and Weidmann, 2015; Manacorda and Tesei, 2020) by highlighting the role of mobile phones in increasing the likelihood of civic engagement and social activities. This study will extent the existing strand of literature that has shown the impact of mobile phones on social and political mobilisation which still rare in Indonesia. Finally, this study contributes to literature on the role of informed voters and government performance (Ferraz and Finan, 2008; Ferraz and Finnan, 2011; Pande, 2011) by showing that villages with better signal strength coverage will have an increased likelihood of participating in political activities such as voting to elect village heads. Studying this context in Indonesia is interesting because to my knowledge, study on the role of media on political activities remains understudied.

Only a small handful of studies have investigated the role of mobile phones on policies. Previous studies have only attempted to investigate the role of mobile phones and their impact on the interaction between voters and their leaders. Grossman et al. (2014) and Grossman et al. (2017) have investigated the role of ICT on the probability that citizens will contact their parliamentary members in Uganda. Both studies have suggested that the introduction of ICT reduces the barrier for citizens to interact with their representatives and increases their political participation. Moreover, Grossman et al. (2014) has observed that marginalised people (e.g. women and poor people) will receive more benefits as a result of easy access to telecommunication and will consequently be more likely to contact their representatives. Furthermore, Grossman et al. (2017) have suggested that implementing a mobilising strategy (e.g. sending texts to voters and encouraging them to participate in political engagement) increases the probability that voters will contact their elected leaders. I build upon these previous papers by showing that not are mobile phones important to citizens' empowerment, but also have a tangible effect on certain policies.

Within the context of Indonesia, studies that investigate the role of media in policy-making are limited. One such study, which is closely related to the present study, is conducted by Olken (2009). This study has explored the impact of television and radio on social capital. Examining data collected from village-level governments in Eastern and Central Java, this study has found that improved television and radio signal reception decreases the amount of social participation at the village level, because people consequently spend more time listening to the radio or watching television. Furthermore, the introduction of television and radio has no significant impact on the number of village meetings or infrastructure creation, which are the proxies for village governance. However, my study shows that mobile phones have different characteristics to radio and television, instead increasing the probability of civic engagement activity.

The distinct differences between a developing country and a developed country in terms of ICT adoption and infrastructure, as well as quality of government, could be an interesting topic of research. This study fills the gaps on the importance of mobile phone usage, as a means not only of increasing political participation, but also improving policies and political leaders' decisions, exploring the extent to which mobile phone usage affects policies, and in which places it significantly contributes. This paper is able to isolate the endogeneity concern of mobile phone adoption by using a relatively new instrument (e.g. lightning strikes) to examine the causal relationship between mobile phones and policies (Andersen et al., 2011, 2012; Manacorda and Tesei, 2020). Finally, this study could explain village leaders' behaviour, which differs from that of other elected and/or appointed policymakers.

The paper proceeds as follows: section 2 provides some institutional background covering both the regulatory and political contexts, as well as the development of ICT in Indonesia; section 3 presents the conceptual framework. Section 4 describes the data specifications. The results are explained in section 5, and section 6 discusses the potential mechanisms of mobile phone effects on policies. Section 7 concludes.

2 Institutional Background

2.1 Village Regulation and Political Context

In 1999, after Suharto's presidency, a major change occurred in the process of democratisation and decentralisation in Indonesia. During the Suharto regime (New Order Era), all decisions were made by the central government, and local governments were controlled and monitored by the central government.[4] Law No. 22/1999 on regional administrations was introduced to provide major reforms in terms of transferring decision-making powers to the district and village governments (Antlöv, 2003; Bebbington et al., 2006).[5]

Many reforms have since been made to local governments and also village-level administrations. As a result, villages are now more autonomous. Indeed, villagers may now elect their village head and are allowed to run their village-owned enterprises. Before 1999, the only source of revenue for the village was via transfers from the district or sub-district governments. Moreover, the village now also has more autonomy to accept or reject programs initiated by the central government (Antlöv, 2003).

Another reform provided by Law No. 22/1999 is the accommodation of cultural diversity within Indonesia's society. Villages can be managed through original customs and local traditions. Villages also have village councils (*Badan Perwakilan Desa*, BPD) that consist of 5 to 13 members and serve as a democratic village body. These village councils have the power to introduce legislation, accept the village budget, and also monitor the village government. In terms of checks and balances, village leaders have to submit a report on an annual basis to the BPD regarding their activities. Therefore, village heads are accountable for the villages' inhabitants, which is quite different from the previous law which stated that the village leaders would report their activities to the district or sub-district governments (Antlöv, 2003).

Recently, the government of Indonesia introduced Law No.6/2014 on village administrations. This is the extended version of the previous regulation related to village governments (Lewis, 2015; Antlöv et al., 2016). The bill attempted to empower village governance, reduce inequality between villages and ensure the effectiveness of the proposed development programs. The major reforms

[4]During President Sukarno's regime, the Indonesian government recognised approximately 250 types of administrative government and community. For example, in Java and Bali, there was *Desa*, *Nagari* in West Sumatra or Minangkabau, *Dusun* and *marga* in South Sumatra (Antlöv, 2003). However, the variation of these types of government did not match the leadership style of his successor, President Suharto, who preferred to exercise strong control over local government. Therefore, in 1979, the government introduced Law No 5/1979, which aimed to impose the same type of institutions across the country. Village-level governments would be controlled and supervised by a higher authority, therefore the village head did not have any ability to implement their own agenda. All decisions were made following the advice of the district or sub-district governments.

[5]The discussion in this subsection is based on Evers (2000), Antlöv (2003), Bebbington et al. (2006) and Antlöv et al. (2016).

in this law are related to central government transfers. The central government will allocate up to 10% of the national budget for transfers to village governments. Moreover, to ensure good governance of the village administrations, this law also increases the power of BPD and introduces village assemblies, which are government bodies that approve or reject the programs proposed by the village heads (Antlöv et al., 2016). The establishment of a village assembly also encourages community participation in the village. Therefore, decision-making at the village level heavily relies on communication between the village communities and the village leaders.

2.2 Village Administrative Institutions

Indonesia has five levels of administrative structure: central government, provincial government, district government, sub-district government and village-level government. In 2014, there were 34 provinces in Indonesia. Each province was divided into two districts: *Kota*, or urban district (98 in 2014) and *Kabupaten* or rural district (416 in 2014) (Ministry of Home Office, 2014). Each district was then further divided into sub-districts known as *Kecamatan*, and finally, the sub-districts were divided into villages, which are the lowest administrative level. Similarly, with districts, there are two types of villages: *Desa* rural and *Kelurahan* urban. In 2014, there were 81,190 villages in Indonesia, of which 72,949 villages (around 89%) are *Desa* and 8,412 villages (around 10%) are *Kelurahan* (Central Bureau of Statistics, 2014).

Desa and *Kelurahan* villages are different in character, especially in regard to government structure. The village head is elected by villagers every six years with a term limit of three periods. On the other hand, the *kelurahan* village leader is appointed by the head of the district government. Furthermore, everyone can become a village leader in the *Desa*. The *Kelurahan* leader, however, must be a civil servant. Therefore, *Desa* and *Kelurahan* are expected to have heterogeneous effects in this study, due to the differences in government structure.

In terms of public goods provisions, villages can provide the goods funded from their budget or from other sources of funding, such as upper-level government (National Development Planning Process or P5D) and donors (e.g. PNPM-Mandiri managed by the World Bank).[6] In 2014, mean village revenues were around Rp 88.8 million (US $5,920), and the total village revenues were around Rp 350.57 million (US $ 23,371).[7] Moreover, almost 48% of the infrastructure programs (e.g. roads, bridges, schools, sanitation, clean water, electricity, clinics, markets and irrigation) implemented at the village level were funded by the village's own budget (Central Bureau of Statistics, 2014). One way for a village leader to increase spending on public goods is by reducing

[6] See Evers (2000) and Martinez-Bravo (2017) for further information.

[7] 1 US $ $\approx$ Rp15000

spending on administration (e.g. salary, meeting expenses, office equipment, etc.) and increasing spending on infrastructure (Martinez-Bravo, 2017).

2.3 Telecommunication Sectors in Indonesia

The development of ICT, especially in the telecommunication sectors in Indonesia, cannot be separated from the Asian financial crisis of 1997-1998. One of the recovery packages proposed by the International Monetary Fund (IMF) stated that the Government of Indonesia had to rescind the monopoly power over Indonesia's state-owned telecommunication company, PT Telekomunikasi Indonesia (Telkom), and remove restrictions on foreign investment.[8] Furthermore, Indonesia joined the World Trade Organisation's Agreement, by which one of their commitments was to urge the country's members to liberalise the telecommunication sectors under the supervision of an independent regulator. The agreement also endorsed the eradication of Telkom's monopoly in the domestic, long-distance, and international telephone markets (Lee and Findlay, 2005).[9]

In 1999, the government of Indonesia passed a new law related to the telecommunications sector (Law No.36/1999), which introduced two important regulations. First, the government would introduce duopoly markets between Telkom and Indosat, and slowly introduce private telecommunications companies into the markets. Second, the restrictions for foreign companies to enter the telecommunication market would be removed (Lee and Findlay, 2005). The (partial) liberalisation of the telecommunication sector resulted in competition between six different providers. In 2016, the largest Indonesian telecommunication companies, based on their market share, were Telkomsel (Telkom subsidiary company) with 77.6% share, XL Axiata with 11.2% share, Indosat with 6.2% share and Hutchison Tri and Smartfren with a combined 5% share (PT Telekomunikasi Selular, 2016). However, no further major reforms have been implemented in Indonesia's telecommunication sector, and there is no significant link between the post-authoritarian period and reform in this sector (Baulch, 2017).

Even though no further reform has been made in the telecommunication sector, it cannot be denied that Law No.36/1999 has significantly transformed Indonesia's ICTs sector. By increasing the number of competitors and providers, the cost to use and to connect over mobile networks has dropped significantly (Lee and Findlay, 2005). As a result, many new telecommunications devices have emerged in the market, making mobile phones more affordable for lower and middle-class

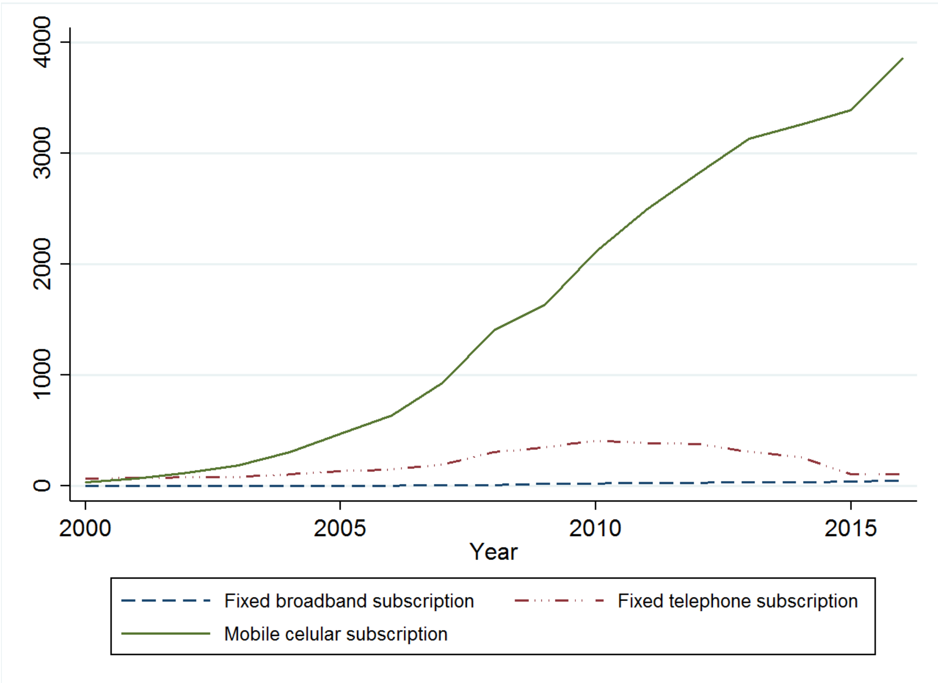
[8]From 1964 to 1989, Indonesia had two state-owned telecommunication companies, PT Telekomunikasi Indonesia (Telkom) and PT Indonesian Satellite Corporation (Indosat). Telkom exclusively provided all domestic services, while international services were monopolised by Indosat. In 1989, due to a lack of funding in the telecommunication sector, the government introduced Law No. 3/1989, which encouraged private investment and established a partnership between Telkom and Indosat for the first time.

[9]See Rohman and Bohlin (2014) for further information on the growth of telecommunication sector in Indonesia

individuals.

Since 2010, almost all Indonesian people have had access to telecommunication, and especially to mobile phones. From Figure 1, it is possible to observe the development of ICT subscriptions in Indonesia. The growth of mobile phone adoption in Indonesia started to surpass the growth of the fixed telephone line in 2002; In 2002, 11.7 million people owned a mobile phone, compared with the 7.7 million people who owned a fixed telephone line. By 2016, the number of people who owned a mobile phone increased to 385.5 million, compared to only 10.3 million people who owned a fixed telephone line. Thus, it is clear that mobile phone subscriptions have grown significantly since 2000, while fixed-line subscription has been steadily declining since 2011. Based on the Intercensal Population Survey (SUPAS), conducted by the Indonesia Central Bureau of Statistics, in 2005, approximately 23% of the population owned a telephone or mobile phone. According to the 2010 Population Census, approximately 76% of the population owned a mobile phone (Minnesota Population Center, 2017).[10]

Figure 1: The Development of ICTs Subscription in Indonesia (in 10,000 People)



Source: International Telecommunication Union, 2017

ICT infrastructure has become a main priority for the government of Indonesia. However, ICT infrastructure is developing slowly, due to a number of problems that the country faces, especially a lack of access to extensive investment. To increase access to telecommunication for all parts of

[10]See also the expansion of mobile phone subscriptions at the village level between 2005 and 2010 in Figure A1 and Figure A2. The figures demonstrate that mobile phone subscriptions have grown significantly. However, in some parts of Indonesia, especially in Eastern Indonesia, the subscription rates were consistently lower for both years. One possible explanation is that the quality of the ICT infrastructure in these areas is relatively poor compared to the rest of the country (See Figure A3.)

Indonesia, in 2005 the government initiated The Indonesian Broadband Plan (IBP), called the Palapa Ring Project, which sought to increase connectivity between islands in Indonesia, both in western and eastern parts, and especially in remote areas. The target of this project is that, by the end of 2019, all areas of Indonesia will be covered and connected by ICT infrastructure (Rohman, 2014).

The association between ICT and policy-making in Indonesia has grown progressively stronger. In 2014, the Ministry of Villages, Disadvantaged Regions and Transmigration introduced call centres that would provide an opportunity for villagers to report their villages' needs or problems. Moreover, one recent example is when the former Governor of Jakarta, Basuki Tjahaja Purnama (*Ahok*), made his mobile phone number public to allow citizens to call or text him if they have a problem that requires government attention. Jakarta has also introduced Qlue, a mobile application that can report and monitor problems faced by Jakarta citizens.[11]

3 Conceptual Framework

In this study, three mechanisms are used to explain how ICTs, specifically mobile phones, affect government policies and/or development. This study focuses on the effect of mobile phones via calls or text messages to the village leader regarding policies. The mechanisms in this study are motivated by the previously outlined studies. Section 6 provides an extensive discussion on the testable mechanisms of this study.

The first mechanism proposed in this study suggest that mobile phones will affect village leaders' policies through an increase in civic engagement, political participation (e.g. voter turnout) and reduce economic rent. Previous studies have shown that mobile phones may affect the probability of political and social participation (see, inter alia, Manacorda and Tesei (2020); Pierskalla and Hollenbach (2013); Shapiro and Weidmann (2015)). The presence of collective action also has a positive effect on political accountability. For example, a study by Devarajan et al. (2011) suggested that there is an improvement in leaders' performance and policy-making in Sub-Saharan countries due to the existence of collective action and civil society. The mechanism proposed here is that villages with higher signal strength will increase the likelihood of having civic engagement activity which will reduce the incentives for the policy-makers to implement rent-seeking policies.

Moreover, due to the presence of a stronger mobile phone signal, it will reduce the incentives to obtain economic rent (Strömberg, 2004b; Besley and Burgess, 2002). Villages with better signal strength will encourage their leaders to perform well and become less corrupt. Here, I propose that village leaders will introduce policies that are beneficial for the majority of society because the

[11] See the website at http://qlue.co.id/site/

increase of information among villagers will exert pressure upon these policymakers to increase their performance. An exchange of information and access to ICT services will increase transparency. From the village leader's perspective, better ICT infrastructure makes them more aware of problems in their village. Because village leaders become better informed, this affects their policy decisions. As previously mentioned, Strömberg (2004b) has found that during the new deal program in the US, governors would increase their spending in areas with higher radio coverage. Besley and Burgess (2002) has found a similar condition in India.

This mechanism will differ from Olken (2009), which found that television and radio have a negative impact on social participation in Indonesian villages. Whereas listening to the radio or watching television are not, in themselves, activities that encourage or enable simultaneous participation in other activities, ownership of a mobile phone presents the individual with the capacity to engage in several activities at once. Another potential channel is civic engagement represents a direct channel to improve living standards. In Indonesia for example, social participation is called *gotong royong*, which is a social activity where people work together to improve their villages' conditions. Mobile phones will play an important role in facilitating the organisation of this social activity. Similarly, another study by Olken (2007) observed that social participation have a little or even insignificant impact on reducing corruption. Thus, having better monitoring procedure does not really reduce economic rents.

The second mechanism posits the hypothesis that mobile phones and media are related to political participation, especially voter turnout (Olken, 2009; Pierskalla and Hollenbach, 2013; Shapiro and Weidmann, 2015; Manacorda and Tesei, 2020). Higher political engagement is associated with political accountability. In this study, I argue that one channel that could affect the improvement in village policy-making is a higher rate of political participation or voter turnout during village elections. Voters will become better informed about their leader's performance and are willing to participate and use their vote to punish or reward the incumbents. This also relates to the literature on the degree to which better informed voters affect political accountability. As it has been suggested by previous studies, technology is associated with a dissemination of information which could affect the probability of civic participation in political activities.

The last mechanism explains the direct link between mobile phones and the village leaders' policies. As has been observed by Grossman et al. (2017) and Grossman et al. (2014), mobile phones reduce the barriers to interaction with government representatives, and therefore increase voters' engagement with them. Adopting the same mechanism, this study assumes that villagers use their mobile phones to interact with their village leader. Therefore, it is easier for a villager to attract their leader's attention when they have better access to ICT, i.e. better ICT infrastructure, and a better signal.

Villagers who are living in areas with better signal strength can maximise the usability of their mobile phone to improve their welfare. On the other hand, villagers who are living in areas with weak signal strength need to meet their leaders directly to inform them of their difficulties. This increases the cost required to inform the village leader of their problems, and consequently decreases the village leader's access to information on the kind of policy the villagers need. Thus, the leader is less likely to implement effective policies, due to a lack of information about the villagers' problems.

Moreover, better signal strength is followed by higher mobile phone subscription rates. Figure A1 and Figure A2 illustrate that areas with a stronger signal (See Figure A3) have higher mobile phone subscriptions compared to area with a weak signal. Therefore, villages with better signal strength exhibit an increase in the number of messages sent from villagers to their leaders. This results in an increase in villagers' consumption of telecommunication products.

It is also expected that there will be heterogeneous effects of ICT between rural and urban villages. Strömberg (2004b) has observed that higher radio penetration has a significant effect on rural areas in the US. Because Indonesia has two types of village government, I also expect that villages with elected leaders will be significantly impacted by the expansion of ICT. Martinez-Bravo (2014) has shown that villages with appointed leaders tend to exhibit clientelistic spending, which affects voters' welfare. Moreover, since village leaders are elected by the villagers (only in *desa*), ICT can also affect their chances of being re-elected, insofar as villages with better ICT infrastructure will be better informed about their leader's performance. This mechanism is also motivated by Strömberg (2004a), Strömberg (2004b) and Snyder Jr and Strömberg (2010), who have found that the amount of information voters receive affects their vote as well as voter turnout. This impact will also be related to the second mechanism, which is the the impact of signal strength on political participation at village elections.

4 Data and Specification

The data used in this study are from the Indonesian Village Potential Statistics (*Potensi Desa*/Podes). These data are collected by the Indonesian Central Bureau of Statistics (*Badan Pusat Statistik*/BPS) every three or four years. The sample of Podes in every census is +/- 65,000 villages across the country. Podes is a census that provides information about Indonesian villages' characteristics, such as government administrations, public goods provided in the village, socio-economic characteristics and other comprehensive information.[12] Because each wave has a different focus, however, some variables are not reported on in all waves of the village census.

In this study, I merge three different waves of the village census, collected from 2008, 2011 and 2014. The main difficulty when constructing this dataset is that The Central Bureau of Statistics in Indonesia uses village identifiers across waves inconsistently. Therefore, some of the villages have a different identifier in different waves. Moreover, the introduction of new villages during the study period is not easily detected. Given the difficulty in merging the dataset with a large number of observations, I chose to use only the villages that are consistently included in all of the waves.[13]

The dataset used in this study consists of 54,602 villages, which cover 33 provinces, 457 districts and 6,292 sub-districts. In total, I have 163,806 observations for this study.[14] Table 1 provides the summary statistics for the data in this study. As previously mentioned, there are different types of government division at the village level. In this study, I use a comprehensive sample of villages in Indonesia, and analyse the results by dividing them according to the different types of government, specifically between *Desa* and *Kelurahan*.

4.1 The Dependent Variables

This study aims to examine whether access to mobile phones increases choice of policies implemented with several mechanism as it has been discussed in section 3. I divide this study into 4 main areas of analysis: (1) the impact of mobile phones on villages' infrastructures; (2) the impact of mobile phones on the improvement of villagers skills via training; (3) the impact of mobile phones on education, especially access to village libraries; and (4) the impact of mobile phones on access to credits.[15]

With regard to the first analysis, I used two dummy variables to capture whether access to mobile phones increases or improves villages infrastructures (e.g. housing, sanitation and clean water). The first dummy variable is **village rehabilitation programs**, which is a binary variable that represents whether the village has a rehabilitation program. From Table 1, it can be observed that the mean for this dependent variable is 0.38, and the standard deviation is 0.49.

[12]In every survey, the enumerator collects the answers from a person who works in the village administration, and verifies this information against the village's administrative records. Some measures of public goods, such as the number of schools, health facilities, mosques, and churches, can be easily verified. Therefore, this survey produces accurate information about the village.

[13]To get villages that are included in all waves, I generate unique Village ID based on province, district, sub-district, and village code. Thus, I will only keep villages that are consistently included in all waves and have similar village id. Villages that are newly established between 2011 and 2014 will be excluded. Another cleaner way to merge PODES is by looking at the Master-File-Desa (MFD) managed by Statistics Indonesia.

[14]While the data does not cover all villages, it covers the majority of Indonesia's population. Specifically, this study covers 54,602 out of 65,000 villages in Indonesia or around 84% of the total number of villages.

[15]Due to the fact that each wave has a different focus, some variables are not available in all years. Only policy and outcome variables that are consistently asked in all Podes waves are used in this study.

Table 1: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Main Variables					
Village rehabilitation programs	163,806	0.38	0.49	0	1
(1 = there is program on village rehabilitation; 0 = otherwise)					
Village rehabilitation programs for poor people	163,806	0.12	0.33	0	1
(1 = there is program on village rehabilitation for poor people; 0 = otherwise					
Capacity building programs	163,806	0.15	0.35	0	1
(1 = village has capacity building programs (e.g. training); 0 = otherwise)					
Capacity building programs for poor people	163,806	0.02	0.15	0	1
(1 = village has capacity building programs (e.g. training) for poor people; 0 = otherwise)					
Village libraries	163,806	0.11	0.31	0	1
(1 = if village has village libraries; 0 = otherwise)					
Credits for small enterprises	163,806	0.20	0.40	0	1
(1 = if village has provided credits for small enterprises; 0 = otherwise)					
Signal	163,806	0.65	0.48	0	1
(1 = signal is very strong; 0 = otherwise)					
Mean flash rate density ($flash\ rate/km^2$)	163,806	16.14	12.26	0	88.91
Other Variables					
Female leader	159,492	0.05	0.21	0	1
Age	159,492	44.25	8.14	17	99
Years of education	159,492	11.77	3.22	0	22
Log population	160,953	7.35	1.16	1.10	12.21
Main source of income	163,806	0.88	0.32	0	1
(1 = agriculture; 0 = others)					
Muslim majority	163,806	0.72	0.45	0	1
Christian majority	163,806	0.39	0.49	0	1
Multi ethnic	163,806	0.73	0.44	0	1
Number of mosques	163,806	7.82	11.83	0	198
Number of churches	163,806	0.88	1.96	0	81
Number of village clinics	163,806	0.29	0.48	0	11
Number of village maternity units	163,806	0.24	0.46	0	14
Number of households with fixed line phone (in 000s households)	163,806	0.07	0.52	0	99.99
Monthly rainfall precipitation (mm)	163,806	119.57	99.63	0	964.91
Additional Informations					
Number of provinces	33				
Number of districts	457				
Number of sub-districts	6,292				
Number of villages	54,602				

The second dependent variable is **village rehabilitation programs for poor people**, which is a dummy variable that represents whether the village has a rehabilitation program but the beneficiaries of this program are exclusively the poor. This dependent variable aims to investigate whether poor people will benefit more from the improvement of ICT sectors. It can be seen that only 12% of the sample has such a program with the standard deviation around 0.33.

For the second analysis, a dummy variable on whether the village has a **training program** (e.g. training for villagers to enhance their skills) becomes the dependent variable. Villages could also have training programs that might improve villagers' skills, which can be used when these people want to apply for a job or to start their own business. The mean for this variable is around 0.15 and the standard deviation is around 0.35. Similar, I introduce another variable (**training programs for the poor**) which represents whether the village has such programs specifically for poor people. The mean for this variable is 0.02 and the standard deviation is approximately 0.15.

For education sectors, access to village libraries will be the outcome. Village governments may build village libraries. The aims of these programs are to increase access to education, especially for pre-preschoolers, and also access to books. Therefore, I introduce a dummy variable on the presence of **village libraries** as the independent variable for the third analysis. The mean for village libraries is around 0.11 and the standard deviation is 0.31.

Finally, as previous studies have shown that access to a mobile phone is associated with access to credit, the last analysis investigates the impact of mobile phones on access to credit, especially credit for small enterprise. **Credit for small enterprise** is a program for people who are planning to start a small scale business (e.g. restaurants, clothing retailers, groceries, among others). Indonesian small and medium enterprises cover almost 97% of domestic employment (OECD, 2018). Here, I use a dummy to establish whether the village has implemented such a program for their villagers. The mean for this program is 0.2 which is slightly higher than for food and agriculture credit programs.

4.2 Explanatory Variables

Publicly available data related to mobile phones in Indonesia is based upon mobile phone signal strength at the village level, which can be collected from Podes and first became available in 2008. [16] In Podes, signal strength is divided into three criteria: (1) no signal, (2) weak signal and (3) strong signal. In this study, the core explanatory variable is *signal strength*, which is a dummy variable that equals one if the village's mobile phone signal is strong. Therefore, the value of the signal will

[16] Other data related to ICTs in Podes include the number of households with fixed line subscription, the existence of public phones, and the number of internet cafes.

be zero if the village's signal strength is weak or non-existent.[17] This variable is different to that used in Olken (2009), which uses the signal strength for television reception. Moreover, the area of study used in Olken (2009) is only Java, whereas my sample extends to almost all the villages in the country.

From Table 1, it is evident that the mean for *Signal* is 0.65 and the standard deviation is 0.48. Thus, almost 65% of the sample villages in the study have a strong signal. Between 2008 and 2014, signal strength improved throughout the villages; whereas the average signal strength was 0.61 in 2008, it rose to 0.68 in 2014. These numbers demonstrate that even though signal strength has improved over this period, around 35% of the sample still have limited access to a strong signal.

Figure A3 depicts the conditions of mobile phone signal strength in Indonesia from 2008 to 2014. Almost all areas in Java are covered by a strong signal, because the ICT infrastructure in Java is significantly better than on the other islands. The majority of Sumatra also has relatively strong signal. Eastern parts of Indonesia, especially Papua, have poor signal strength, however. This is because the infrastructure quality in the eastern part of Indonesia is generally worse than on the other islands. It is also clear that from 2008 to 2014, signal strength greatly improved, especially in Java and Sumatra.

4.3 Specification and Identification Strategy

In this study, two main econometric methods are used to examine the impact of mobile phone usage on policies: (1) a linear probability model (LPM) and (2) a probit model.

The linear probability model is as follows:

$$Y_{v,t} = \beta Signal_{v,t} + \gamma X_{v,t} + \theta_v + \vartheta_t + \epsilon_{v,t} \tag{1}$$

where $Y_{v,t}$ is the binary dependent variable in the village v at time t. $Signal_{v,d,t}$ is a dummy variable that has a value of 1 if the village v and time t have a strong mobile signal, and 0 otherwise; $\gamma X_{v,t}$ represent the vector of control variables; θ_v are the village fixed effects; and ϑ_t are the year fixed effects. The main coefficient of interest is β, because it estimates the within-village difference in the probability of the dependent variable being 1 (Pr ($Y_{v,t}$ = 1)), between villages with strong versus weak and non-existent signals that exhibit similar characteristics.

The control variables used in this paper are the set of rich datasets related to village-level characteristics, such as variables related to village governance, e.g. female leader (i.e. 1 if female, 0

[17] This is the margin that seems to have the strongest effect for these three categories. In the robustness check, I also test using two dummies (e.g. strong signal and no signal) (See Table 8) and categorical signal strength (See A2).

otherwise), age, years of education; village-level demographic, e.g. log of population, main sources of income (i.e. 1 if agriculture, 0 otherwise) and social indicators, e.g. Muslim majority (i.e. 1 if Muslim majority, 0 otherwise), Christian majority (i.e. 1 if Christian majority, 0 = otherwise), multi-ethnic (i.e. 1 if more than one ethnicity, 0 otherwise), number of mosques, number of churches, number of village clinics, number of village maternity units, number of households with a fixed line phone. The list of control variables for the village-level characteristics is displayed in Table 1.

The second method is the probit model, estimated via the following equation:

$$Pr(Y_{v,t} = 1) = F(\beta Signal_{v,t} + \gamma X_{v,t} + \theta_v + \vartheta_t + \epsilon_{v,t}) \tag{2}$$

where $F(.)$ is the cumulative distribution function of the standard normal distribution.[18]

The results from the LPM and probit estimations might be biased, however, because the signal strength variable might not be entirely random (Angrist and Krueger, 2001; Angrist and Pischke, 2009; Wooldridge, 2010). As has been shown by previous studies in related literature, mobile phone signal strength might be endogenous and non-random (Aker and Mbiti, 2010; Manacorda and Tesei, 2020). Areas with larger populations or better infrastructures and income levels might have better signal strength. However, the large number of high buildings in the surrounding area could also negatively affect mobile phone signal. This condition could also make signal strength endogenous, because the decision to install telecommunication infrastructures might be correlated with the error term which could also affect outcome variables in this study. For example, Indonesia regularly faces many natural disasters (e.g. earthquakes, volcanic eruption, etc.). An expectation of such events would reduce the incentives for telecommunication services to invest their infrastructures in areas with higher probability of facing natural disasters, leading to worse signal strength, and associated outcomes. This concern would potentially underestimate (downward bias) the estimations from OLS or probit methods.[19] Finally, reverse causality may also bias our result because it is possible that areas with better social development conditions will also have a good presence of mobile phones signal.

Our last potential problem that could bias the results is the measurement error of signal strength. The data on signal strength is based on the answers provided by the village administrations and, thus, may not accurately reflect the true condition of mobile phone signal strength. There is a higher

[18] Logit and Probit, however, exhibit several limitations when using fixed effects. See Heckman (1979) and Greene (2004) for further explanation.

[19] Another concern that may affect the empirical results in this study is attrition bias due to a small part of villages from PODES are excluded from our samples. Attrition bias may affect our estimation results due to sample selection bias. To isolate this, a battery of covariate has been used in our model which has been explained in equation (1) such as village level characteristics. Nonetheless, it seems that there might be other factors that will bias our estimates from unobserved factors.

probability that the information for the signal strength might be over reported, which could again bias the estimations (Hausman, 2001). I will use instrumental variable strategy to deal with these concerns.

4.4 Instrumental Variable

Although an instrumental variable strategy could be used to solve the problem with endogeneity, it is quite difficult to find exogenous variables that would work in this study. As noted by Aker and Mbiti (2010), the issue with ICT studies is that it can be difficult to find a credible instrumental variable. In this study, what we need is a variable that captures and exploits the variation in mobile phone signal strength coverage across villages and years. One possible variable is the plausibly exogenous factor of different lightning strike incidence (or flash rate, I will use these terms interchangeably).

The mechanism on why lightinig strikes affect mobile phone signals is the following: lightning strikes have strong relationship with the provision and quality of telecommunication infrastructure. Andersen et al. (2012) and Manacorda and Tesei (2020) have observed that lightning strikes can damage telecommunication transmitters. This can result in less investment in telecommunication towers because it will be very expensive to invest in areas with higher risks of lightning strikes. Telecommunication providers will avoid putting physical infrastructures in such areas, thus reducing of mobile phone signal strength. Therefore, in order to be a valid instrument, higher flash rate intensity will slow down the adoption of mobile phone devices and I expect that villages with higher flash rate intensity will have lower mobile phone signal strength. The underlying assumption here is that the variation of flash rate intensity only affects the dependent variables through the growth of ICT coverage.

I use the mean of lightning strike intensity per km^2 between 1998 and 2013 at the village level, as the instrument (Andersen et al., 2011, 2012; Manacorda and Tesei, 2020).[20] The data is available across the world and, in this study, I was able to construct the flash incidence data at the Indonesian village level. Because the data provided by NASA is the average between 1998 and 2013 and therefore time invariant, I used the interaction between flash rate intensity for the village v and time trends to allow me to estimate the effects of the instrument on mobile phone signal strength in the panel data setting. The use of the interaction term generates a continuous difference-in-differences

[20]Data retrieved from LIS 0.1 Degree Very High Resolution Gridded Lightning Full Climatology (VHRFC) https://ghrc.nsstc.nasa.gov/hydro/details/lisvhrfc. This data is provided by the US National Aeronautics and Space Administration (NASA). The data is the average flash rate between 1998 and 2013 and, therefore, is time invariant. Andersen et al. (2012) and Manacorda and Tesei (2020) have determined that a consistent pattern exists for lightning strikes across this period of time. See Cecil et al. (2014) for further information.

estimator that is able to identify the causal effect of time invariant variation from the flash rate intensity (Angrist and Imbens, 1995; Angrist, 1998). This interaction term will also capture the trend of increased mobile phone adoption across different villages. A similar approach has been used by Manacorda and Tesei (2020), where the interaction between flash rate incidence and time trends functions as an instrument for measuring mobile phone coverage in Africa.

Hence, the first stage of this estimation is:

$$Signal_{v,t} = \alpha_{v,t} + Z_{v,t} + \gamma X_{v,t} + \theta_v + \vartheta_t + \mu_{v,t} \tag{3}$$

where $Z_{v,t} = Flash\ rate_v * time\ trend$. I also include the set of control variables $\gamma X_{v,t}$, which is the same as the covariate in equation 1, as well as village fixed effects (θ_v) and year fixed effects (ϑ_t).

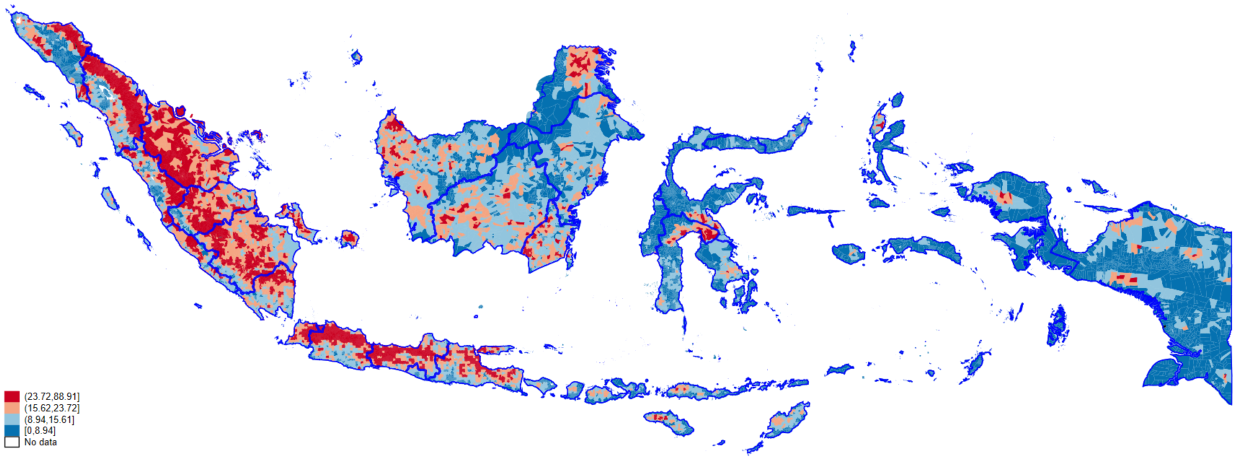
The underlying identification behind this instrument relies on the assumption that the village policies would not change over time unless due to the variation of the mobile phone signal, which is due to the intensity of lightning strikes and interaction with a time trend. Therefore, when I interpret the coefficient for $Z_{v,t}$ for the first stage results, higher incidence of lightning strikes is expected to lead to a slower improvement of mobile phone signal.

A critical reader will then ask why this is a credible instrument and what are the problems with this instrument? First, let me explain why this is a good instrument for measuring mobile phone coverage, especially in the context of Indonesia. Indonesia has a higher flash rate incidence due to its location and geographical characteristics. Cecil et al. (2014) have suggested that tropical and sub-tropical regions tend to have a higher annual flash rate. Albrecht et al. (2011) have also observed that high flash rates are linked to topographical features.

Figure 2 depicts the variation of lightning strikes in Indonesia between 1998 and 2013. Based on the Figure, areas in Sumatra have higher incidences of lightning strikes. Most of this area is located at a higher altitude. Moreover, some parts of Java also exhibit higher lightning strike incidences. One thing worth nothing is the high variation of lightning strikes across the country, which can be important to explain the variation in signal strength throughout Indonesia. The mean flash rate in Indonesia from 1998 to 2013 was 16.14 flash rate/km^2 (See Table 1). This number is higher than the global flash rate, which is around 2.9 flash rate/km^2, and the average flash rate in the tropics and sub-tropics (10 flash rate/km^2).

Even though I am relying on the assumption that flash rate intensity is potentially exogenous and will affect policy only through the slower improvement of mobile phone signals, there are several concerns that arise from using this variable, especially related to the exclusion restrictions. First, as has been shown in Figure 2, lightning strike intensity is clustered and may be correlated

Figure 2: Mean Annual Flash Rate Density between 1998 and 2013 (Flash Rate/km^2)



Source: Author's calculation from Cecil et al. (2014)

with geographical features (e.g. topography). Even though I estimate the model by including several village fixed effects that could capture this, geographical features could affect decisions over the placement of other infrastructures and therefore affect our outcomes. Second, areas with higher flash rate incidences might also have a higher probability of correlation with other natural disasters (e.g. storms or rains) which could affect the outcomes. This again leads to the violation of our identification assumption for the exclusion restriction. Third, it is possible that there is a new technology which is unobservable and could minimise the impacts of lightning strikes on mobile phone signals. All of these issues might raise some concerns with our identification strategy. Finally, because the flash rate is adopted from the satellite image, measurement error may be a concern here. Thus, violate the use of the instrument.

In order to at least mitigate some of these problems, I use a battery of control variables used in the baseline specifications and also include village fixed effects which will capture the time invariant village characteristics (e.g. elevation, latitude, longitude). Moreover, to isolate the concern over the correlation between topographical features and flash rate intensity, I use topographical (1=land, 2=valley, and 3=hill) by-year fixed effects. Because the flash rate might be correlated with storms or rains, I also use the index for rain precipitation at the village levels. By applying all of these strategies, the underlying assumption of using flash rate intensity as the instrument variable will be validated and the exclusion restriction will be plausible, conditional on the inclusion of a full set of covariates and several fixed effects to control some unobservable time invariant village characteristics.

5 Results

In this section, I discuss the results from the LPM and Probit estimations of equation 1 and equation 2. I begin the analysis by discussing the association between signal strength and the policies made by village leaders. I also discuss the results from 2SLS estimates of equation 3. Later, I will elaborate the potential extension and robustness tests.

5.1 LPM and Logit Results

Village Rehabilitation Programs. Table 2 exhibits the estimation results for the village rehabilitation programs. The dependent variable in this table is the dummy variable, which has a value of 1 if the village has a rehabilitation program, and 0 otherwise (columns 1 - 4) and the dummy variable, which has a value of 1 if the village has a rehabilitation program specifically for poor people (columns 5 - 8).

Table 2: Baseline Results: Village Rehabilitation Programs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Village Rehabilitation Programs				Village Rehabilitation Programs for Poor People			
Signal strength	0.0052	0.0054	0.0054	0.0016	0.016***	0.014***	0.013***	0.0090***
	(0.0039)	(0.0040)	(0.0040)	(0.0027)	(0.0027)	(0.0028)	(0.0028)	(0.0020)
N	163806	156506	156506	156745	163806	156506	156506	156745
R^2	0.468	0.479	0.480		0.387	0.403	0.403	
pseudo R^2				0.098				0.050
Estimation method	LPM	LPM	LPM	Probit	LPM	LPM	LPM	Probit
Village FE	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Urban by Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Topography by Year FE	No	No	Yes	No	No	No	Yes	No
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Mean dep. var.	0.38	0.38	0.38	0.38	0.12	0.12	0.12	0.12

* Notes: Robust standard errors in parentheses and clustered at the village levels. The dependent variables in this estimation are dummy variable for village rehabilitation programs at the village level (columns 1 - 4) and dummy variable for village rehabilitation programs where the beneficiaries are only poor people (columns 5 - 8). Time varying controls: log population, log (1+night light), dummy for female leader, leader's age, leader's years of education, main source of income, dummy for Muslim majority, dummy for Christian majority, dummy for multi ethnic, number of mosques, number of churches, number of village clinics, number of village maternity units, number of households with fixed line phone, distance to district and distance to sub-district. Urban (1 = urban; 0 = otherwise), topography (1 = land, 2 = valley, 3 = hill), . The years included in the regressions are 2008, 2011 and 2014. Columns (4) and (8) are the marginal effects for probit estimation methods. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Let me start by analysing the result for village rehabilitation. Column (1) provides the linear probability model for this dependent variable. It suggests that by only controlling for village and year fixed effects, signal strength does not have any affect on village rehabilitation programs. Similarly, in column (2), even after including covariates we still do not observe any impact of signal strength on our outcomes. Similarly, in column (3) once I controlled for topography by-year fixed effects, which capture the different time trends for different district levels, the result does not suggest higher signal strength is associated with having village rehabilitation programs. Furthermore, in column (4) the probit model suggests no relationship between signal strength and village rehabilitation programs.

Moving to a similar program which is specifically implemented for poor people, column (5) suggests that a strong signal is associated with higher probability of having rehabilitation programs for poor people. Even after controlling for time variant covariates (column 6) and district by-year fixed effects (column 7), the point estimate suggests that a strong signal leads to a higher probability of the improvement of village conditions specifically for poor people, statistically significant at 1%. The marginal effect from the probit model also suggests that a strong signal increases the outcome by 0.9 percentage points and is statistically significant at 1%. However, because I do not control for time invariant village characteristics in this model, we cannot isolate the within-village variation and may create omitted variable bias.

These results are consistent with my hypothesis that an increase in access to ICT will increase a village leader's incentive to implement policies that are beneficial to the people, even though only to village rehabilitation programs for poor people.

Capacity Building Programs. The association between signal strength and training to increase villagers' skills is presented in Table 3. In column (1), regressing the capacity building dummy on signal strength without including any covariates does not have any meaningful statistical evidence. Controlling for some covariates in column (2) also suggests that signal strength does not have any relationship with capacity building programs. Similarly, once controlled by district by-year dummies (column 3), it shows that signal strength do not affect the probability of the presence of training programs. The estimation result from the probit model suggests that higher signal strength is associated with higher probability of the village having such a program. However, we cannot isolate the possibility of omitted variable bias because it is estimated without controlling for village time invariant characteristics.

Even though the evidence suggests that mobile phones have no association with capacity building programs, it is interesting to see whether the result would be different for the same program where the beneficiaries are poor people. Columns (5) - (8) provide the estimation results for the new dependent variable. We can see that from the linear probability model, the results are statistically insignificant for all specifications (columns 5 - 7). The marginal effect estimation result from the

Table 3: Baseline Results: Capacity Building Programs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Capacity Building Programs				Capacity Building Programs for Poor People			
Signal strength	0.0015	0.0022	0.0024	0.032***	0.00036	0.000095	0.000046	0.0052***
	(0.0027)	(0.0028)	(0.0028)	(0.0022)	(0.0012)	(0.0012)	(0.0012)	(0.0011)
N	163806	156506	156506	156745	163806	156506	156506	156745
R^2	0.431	0.445	0.445		0.354	0.368	0.368	
pseudo R^2				0.090				0.049
Estimation method	LPM	LPM	LPM	Probit	LPM	LPM	LPM	Probit
Village FE	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Urban by Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Topography by Year FE	No	No	Yes	No	No	No	Yes	No
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Mean dep. var.	0.15	0.15	0.15	0.15	0.02	0.02	0.02	0.02

* Notes: Robust standard errors in parentheses and clustered at the village levels. The dependent variables in this estimation are dummy variable for village capacity building programs at the village level (columns 1 - 4) and dummy variable for village capacity building programs where the beneficiaries are only poor people (columns 5 - 8). Time varying controls: log population, log (1+night light), dummy for female leader, leader's age, leader's years of education, main source of income, dummy for Muslim majority, dummy for Christian majority, dummy for multi ethnic, number of mosques, number of churches, number of village clinics, number of village maternity units, number of households with fixed line phone, distance to district and distance to sub-district. The years included in the regressions are 2008, 2011 and 2014. Columns (4) and (8) are the marginal effects for probit estimation methods. $^* p < 0.10$, $^{**} p < 0.05$, $^{***} p < 0.01$

probit model in column (8) suggests signal strength is positively correlated with capacity building programs for poor people. Without controlling for unobservable time invariant village characteristics, we can interpret that higher mobile phone signal coverage is associated with an increase in the likelihood of program implementation by 0.5 percentage points, statistically significant at 1%.

Village Libraries and Access to Credit. Table 4 provides the estimation results for the dummy for village libraries and the implementation of providing credits for small enterprises. Columns (1) - (4) depict the results for village libraries. In column (1), the result of the linear probability estimation method without controlling for any time variant covariates suggests that there is robust evidence that signal strength increases the probability that a village will possess a library. The same results can be observed in column (2) even after including control variables. In the most demanding specification in column (3), signal strength increases the likelihood that a village will possess a library by 0.64 percentage points, statistically significant at 1%. The marginal effect from the probit method also suggests that a stronger mobile phone signal is associated with an increase in the presence of village libraries by 2.7 percentage points.

The results for credits for small enterprises are shown in columns (5) - (8). In general, different specification methods suggest robust evidence that higher signal strength is associated with higher probability of having access to credit. In column (5), regressing the dependent variable on the

Table 4: Baseline Results: Village Libraries and Access to Credit

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Village Libraries				Credits for Small Enterprises			
Signal strength	0.0071***	0.0064***	0.0064***	0.027***	0.017***	0.015***	0.015***	0.071***
	(0.0022)	(0.0023)	(0.0023)	(0.0022)	(0.0030)	(0.0031)	(0.0031)	(0.0024)
N	163806	156506	156506	156745	163806	156506	156506	156745
R^2	0.500	0.512	0.512		0.489	0.501	0.501	
pseudo R^2				0.124				0.124
Estimation method	LPM	LPM	LPM	Probit	LPM	LPM	LPM	Probit
Village FE	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Urban by Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Topography by Year FE	No	No	Yes	No	No	No	Yes	No
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Mean dep. var.	0.11	0.11	0.11	0.11	0.20	0.20	0.20	0.20

* Notes: Robust standard errors in parentheses and clustered at the village levels. The dependent variables in this estimation are dummy variable for village libraries at the village level (columns 1 - 4) and dummy variable for credits for small enterprises where the beneficiaries are only poor people (columns 5 - 8). Time varying controls: log population, log (1+night light), dummy for female leader, leader's age, leader's years of education, main source of income, dummy for Muslim majority, dummy for Christian majority, dummy for multi ethnic, number of mosques, number of churches, number of village clinics, number of village maternity units, number of households with fixed line phone, distance to district and distance to sub-district. The years included in the regressions are 2008, 2011 and 2014. Columns (4) and (8) are the marginal effects for probit estimation methods. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

signal strength without any covariates, the point estimate for signal strength is around 0.017 and statistically significant at 1%. Even after including covariates in column (6) and also controlling for district by-year trend in column (3), the point estimates are relatively similar and still statistically significant at 1%. Finally, the estimation result from the probit model also suggests that signal strength has a positive relationship with access to credit. In terms of the magnitude, from the most demanding specification in column (7), higher signal strength increases the likelihood of credit programs for small enterprises by 1.5 percentage points.

In general, the results from the LPM and Probit exercises suggest that signal strengths have effects on some policies and are very important for poor people. However, as has been mentioned before, we still have some endogeneity issues with the estimation results that probably could bias the results. In the next section I will provide the results from the two stage least square (2SLS) estimations to address these concerns.

5.2 Instrumental Variable

I performed a 2SLS estimation to address the endogeneity problem with previous estimations. As mentioned previously, the flash rate intensity is used as an instrument for signal strength. Before analysing the results from the 2SLS estimation, let us see whether the instrument has any relevance to the signal strength. Table 5 depicts the first stage estimation results, where the dependent variable is signal strength and the independent variable is the incidence of lightning strikes at the village levels interacting with a time trend. Column (1) is estimated without including any covariates and column (2) is estimated by including several covariates, including precipitation. All covariates used here are similar to those used in the previous tables. I also include village and year fixed effects and also topography by-year fixed effects.

I expect the association between the flash rate intensity $\times$ a time trend and the signal strength will be negative. In other words, we can anticipate a slower growth of mobile coverage in areas with higher flash rate intensity, which will be exploited by the flash rate intensity $\times$ a time trend interaction. The first stage results indicate that the instrument reduces the signal strength and is statistically significant at 1% for different specification methods. In terms of the magnitude, a one standard deviation increase in the instrument is associated with a decrease in the signal strength by 1.71 percentage points (29.578 $\times$ -0.00058 $\times$ 100). The instrument also passes the standard test for validity, as the joint-F statistics of the Kleibergen-Paap test for weak identification for this instrument range from 44.76 to 89.92 (Staiger and Stock, 1997).

The results for the reduced form in Table A1 also suggest that the instrumental variable in this study have a strong reduced form relationship with the outcome variables, except capacity building programs and also capacity building program for poor people. This is similar to what I have observed in Table 3, where capacity building programs and capacity building programs for poor people are not improved due to a strong presence of mobile phones signal.

Moving to the 2SLS estimation results, Table 6 contains all the results for the dependent variables in this study. Village and year fixed effects are included in all columns, as well as topography by-year fixed effects. I also employ the same covariates used in the LPM and Probit estimation methods and the precipitation index. Again, as expected, the results from the first stage suggest that the instrument in this study has a robust and negative relationship with the signal strength. The joint-F statistics of the Kleibergen-Paap test for weak identification do not show that this instrument is weak. The F-test is also higher than the critical value from Stock-Yogo method.

For the interpretation of the 2SLS estimation methods, in column (1) for village rehabilitation programs, we can see that the 2SLS method suggests that higher signal strength is associated with higher probability of the presence of village rehabilitation programs by 1.57 or 157 increase in percentage points and this is statistically significant at 1%. In column (2) we also see robust statistical evidence that signal strength increases the probable incidence of village rehabilitation programs by 1.26 or 126 increase in percentage points where the beneficiaries are poor people. Both these results support the evidence obtain from the baseline specification in Table 2.

Table 5: Instrumental Variable Estimations: First Stage

	(1) Signal Strength	(2) Signal Strength
Flash rate intensity × time trend	-0.00077***	-0.00057***
	(0.000082)	(0.000087)
N	163806	156506
R^2	0.662	0.671
Village FE	Yes	Yes
Year FE	Yes	Yes
Topography by Year FE	Yes	Yes
Urban by Year FE	Yes	Yes
Controls	No	Yes
First Stage		
F	87.81	43.27
Stock-Yogo Critical Value	16.38	16.38

* Notes: The years included in the regressions are 2008, 2011 and 2014. Signal strength is instrumented by mean annual flash rate density per km^2 between 1998 and 2013 in a village interacting with a linear time trend. Time varying controls: log population, log (1+night light), dummy for female leader, leader's age, leader's years of education, main source of income, dummy for Muslim majority, dummy for Christian majority, dummy for multi ethnic, number of mosques, number of churches, number of village clinics, number of village maternity units, number of households with fixed line phone, distance to district, distance to sub-district and rain precipitation. See Table 2 for further information. Robust standard errors in parentheses and clustered at the village levels. The F statistic for the first stage is the F-statistic of the Kleibergen-Paap rk Wald test for weak identification. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

For the capacity building programs, both columns (3) and (4) suggest that mobile phone signal does not affect the likelihood of implementing the programs. This is also consistent with the evidence observed from the LPM method, where I do not find any statistical evidence to indicate whether signal strength will affect the likelihood of having these programs. One possible explanation for these results is that village heads might prefer to improve the quality of infrastructure rather than providing training because the beneficiaries of village improvement will be larger in scope than would be the case for training schemes targeted at specific individuals.

The evidence for village libraries in column (5) also suggests that signal strength is associated with a higher probable incidence village libraries and is significant at 1%. Stronger mobile phones signal will increase the availability of village libraries by 51 percentage points. Finally, in column (6), the result from the 2SLS method suggests that strong mobile phone signal coverage is associated with an increase in the probability that policies will be implemented in relation to credit for small enterprises, statistically significant at 5%. These results also suggest that villagers and village chiefs consider an improvement in access to education and credit to be very important.

The results from the 2SLS estimation method indicate that signal strengths have a causal effect on some outcomes in this study. Yet we can see that the point estimates from the 2SLS estimation methods are significantly higher than those obtain from the LPM and Probit methods. There are

Table 6: Two Stage Least Square Estimations: All Dependent Variables

	(1) Village Rehabilitation Prog.	(2) Village Rehabilitation Prog. for Poor People	(3) Capacity Building Prog.	(4) Capacity Building Prog. for Poor People	(5) Village Libraries	(6) Credit for Small Enterprises
Signal strength	1.57***	1.26***	0.021	-0.11	0.51***	0.43**
	(0.31)	(0.24)	(0.16)	(0.071)	(0.16)	(0.18)
N	156506	156506	156506	156506	156506	156506
Estimation method	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Village FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Urban by Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Topography by Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
First stage						
Flash rate intensity	-0.00058***	-0.00058***	-0.00058***	-0.00058***	-0.00058***	-0.00058***
× time trend	(0.000087)	(0.000087)	(0.000087)	(0.000087)	(0.000087)	(0.000087)
F	43.27	43.27	43.27	43.27	43.27	43.27
Stock-Yogo Critical Value	16.38	16.38	16.38	16.38	16.38	16.38
Mean dep. var.	0.38	0.12	0.15	0.02	0.11	0.20

* Notes: Robust standard errors in parentheses and clustered at the village levels. The years included in the regressions are 2008, 2011 and 2014. Signal strength is instrumented by mean annual flash rate density per km^2 between 1998 and 2013 at the village level interacting with a linear time trend. Time varying controls: log population, log (1+night light), dummy for female leader, leader's age, leader's years of education, main source of income, dummy for Muslim majority, dummy for Christian majority, dummy for multi ethnic, number of mosques, number of churches, number of village clinics, number of village maternity units, number of households with fixed line phone, distance to district, distance to sub-district and rain precipitation. See Table 2 for further information. The F statistic for the first stage is the F-statistic of the Kleibergen-Paap rk Wald test for weak identification. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

several explanations for these results. The first of these is the problem with the measurement error from the signal strength, which biases the LPM and Probit estimates of the effect from the signal strength toward zero (downward bias). Since, the 2SLS or IV estimate is unaffected by the measurement error in the endogenous variable, the point estimates tend to be larger than the LPM/Probit estimates (Angrist and Krueger, 2001; Hausman, 2001). Second, the IV estimates the local average treatment effect (LATE) of the change in signal strength *only* for the sample in which choice of the treatment was affected by the instrument. Therefore, the point estimates for IV will be significantly higher, because in this case it estimates the *average* difference in outcomes due to the variation in the signal strength.

Finally, even though I have included several covariates to minimise the problem with the exclusion restrictions, it is possible that the instrument is still correlated with something unobservable in the error term. Nevertheless, the results from the diagnostic test and the first stage relationship between the instrument and the explanatory variable conditional on a battery of control suggest that the instrument passes the requirements to be a valid instrument. It also shows that we can disregard any concerns over the possibility of a weak instrumental variable in this study.

5.3 Extensions

Desa versus Kelurahan. In the previous section, I discussed the differences between *Desa* and *Kelurahan* in terms of administrative characteristics. In this section, I further differentiate the sample into two groups: *Desa* village and *Kelurahan* village. Table 7 presents the results of this analysis.

Table 7: Additional Results: Desa versus Kelurahan

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Village Rehabilitation		Village Rehabilitation for Poor People		Capacity Building		Capacity Building for Poor People		Village Libraries		Credit for Small Enterprises	
Signal strength	1.96***	-0.075	1.61***	3.04	-0.91***	8.96	-0.20*	0.28	0.36	5.34	0.59**	0.46
	(0.65)	(2.29)	(0.50)	(3.15)	(0.35)	(8.24)	(0.11)	(1.17)	(0.22)	(5.30)	(0.28)	(2.35)
N	139110	16867	139110	16867	139110	16867	139110	16867	139110	16867	139110	16867
Estimation method	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Sub-district FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Topography by Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Desa	Kelurahan	Desa	Kelurahan	Desa	Kelurahan	Desa	Kelurahan	Desa	Kelurahan	Desa	Kelurahan
First stage												
Flash rate intensity	-0.00027**	-0.000097	-0.00027**	-0.000097	-0.00027**	-0.000097	-0.00027**	-0.000097	-0.00027**	-0.000097	-0.00027**	-0.000097
× time trend	(0.000079)	(0.000086)	(0.000079)	(0.000086)	(0.000079)	(0.000086)	(0.000079)	(0.000086)	(0.000079)	(0.000086)	(0.000079)	(0.000086)
F	54.07	1.25	54.07	1.25	54.07	1.25	54.07	1.25	54.07	1.25	54.07	1.25
Stock-Yogo Critical Value	16.38	16.38	16.38	16.38	16.38	16.38	16.38	16.38	16.38	16.38	16.38	16.38

[*] Notes: Robust standard errors in parentheses and clustered at the village levels. The dependent variables in this estimation are dummy variable for village rehabilitation program at the village level (columns 1 - 2), dummy variable for village rehabilitation programs where the beneficiaries are only poor people (columns 3 - 4) dummy variable for village capacity building program at the village level (columns 5 - 6); dummy variable for village capacity building programs where the beneficiaries are only poor people (columns 7 - 8); dummy variable for village libraries (columns 9 - 10) and dummy variable for credit for small enterprises (columns 11 - 12). The F statistic for the first stage is the F-statistic of the Kleibergen-Paap rk Wald test for weak identification. See Table 2 and Table 6 for further information. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

For each variable, odd numbered columns are the estimation results for *desa* and even numbered columns are the results for *kelurahan*. In this table, instead of using village fixed effects, I use sub-district (*kecamatan*) fixed effects to capture the difference between *desa* and *kelurahan* within the same sub-districts with similar characteristics. Moreover, I use the 2SLS estimation methods for the analysis.

Before I analyse the second stage results, the standard diagnostic test for the instrumental variable strategy suggests that there is a negative and statistically significant relationship between the instrument and signal strength when I restrict the sample to *desa* only. However, I do not find any first stage relationship when I only use the sample for *kelurahan*. Similarly, the F-statistics of the Klebergen-Paap test for *desa* is around 54.07 (Stock-Yogo critical value ≈ 16.38 but we have a weak instrument issue for *kelurahan* (F-statistics = 1.25). This problem might occur because the sample for *kelurahan* is significantly lower compare to *desa* (12.12% relative to *desa*). Due to this, we only focus our result for the *desa* only.

For village rehabilitation programs, column (1) in Table 7 suggests that signal strength in *desa* villages is associated with higher likelihood of having such a program. In columns (3), again I find that signal strength has a positive and statistically significant relationship with the implementation of village rehabilitation for poor people in *desa*.

The interesting finding here relates to *desa* villages, where both capacity building (column 5) and capacity building programs for poor people (column 7) have negative relationships with signal strength, even though it is less significant for the latter. This finding for *desa* is quite different with what I find in the full sample. There is no obvious explanation for this finding, but it seems again that village heads prefer policies that will benefit the whole society rather than just a small number of people.

Finally, I do not find any differences in terms of the provision of village libraries (columns 9 - 10) for either *desa* or *kelurahan*. Both columns show that the coefficients on signal strength for each sample are not statistically significant. Finally, for access to credit in columns (11) and (12), the 2SLS estimates that signal strength increases the probability of the implementation of the program in *desa*. This evidence suggests that mobile phone adoption will benefit rural areas, which is consistent with previous studies on the relationship between access to technology and credit (Aker and Mbiti, 2010).

In summary, there is clear evidence that the association between mobile phone signal and the outcome variables is stronger in *desa*. For *kelurahan*, however, there is not enough evidence on the relationship between these variables. There are some explanations for these findings. First, the fact that in *desa*, due to its rural characteristics and lack of facilities, major improvements in some policies are essential; also, I do not have a sufficiently large sample size or statistical power for *kelurahan* and therefore cannot draw any meaningful inference in relation to this sample.

Second, this result could be explained by the fact that village leader in *desa* has relatively more power and, thus, ability to implement policies than the leader of *kelurahan*. Third, *desa* villages do not have many alternative options through which to contact their leader. Once they have access to better mobile phone signal strength, it is easier for them to request assistance from their leaders. Finally, small sample size for *kelurahan* may yield these findings.

Robustness Check. I performed a robustness check by introducing two dummy variables (*strong signal and no signal*) as an alternative explanatory variable. This variable has a value of 1 if the signal strength is strong for strong signal dummy and 0 if otherwise. Similarly, it has value of 1 if there is no signal for no signal dummy and 0 if otherwise. This exercise could explain which variable drives the outcomes more strongly. [21] Table 8 presents the results for these new variables. The LPM model was used to test this query.

The result for village rehabilitation programs in column (1) suggests that both strong and no signal strength affect the likelihood of having such a program. Strong signal has a positive and weakly significant relationship with the dependent variable and on the other hand, no signal strength reduces the likelihood of a village having the program by 1.5 percentage points. In column (2), I find that the implementation of the program for poor people is negatively associated with

[21] The use of strong signal and no signal to see the monotonicity of the main independent variable on our policy variables. Nonetheless, the result for strong versus weak signal can be seen in Table A6. The result from Table A6 suggests that strong signal affects our policy variables more stronger compared to the weak mobile phones' signal.

Table 8: Additional Results: Strong versus No Signal

	(1) Village Rehabilitation	(2) Village Rehabilitation for Poor People	(3) Capacity Building	(4) Capacity Building for Poor People	(5) Village Libraries	(6) Credit for Small Enterprises
Strong signal strength	0.0075*	0.0031	0.0052*	0.0000036	0.0079***	0.0100***
	(0.0040)	(0.0027)	(0.0029)	(0.0013)	(0.0023)	(0.0032)
No signal strength	-0.015**	-0.016***	0.0024	0.0013	0.0022	-0.011***
	(0.0067)	(0.0047)	(0.0040)	(0.0018)	(0.0031)	(0.0040)
N	156502	156502	156502	156502	156502	156502
R^2	0.524	0.482	0.481	0.392	0.536	0.521
Estimation method	LPM	LPM	LPM	LPM	LPM	LPM
Village FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
District by Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Topography by Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

* Notes: Robust standard errors in parentheses and clustered at the village levels. The years included in the regressions are 2008, 2011 and 2014. Strong signal strength will be equal to 1 if signal strength is strong and 0 if otherwise. No signal strength will be equal to 1 if there is no signal and 0 if otherwise. Time varying covariates in this table are the same with covariates used in Table 2. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

no signal strength. However, I do not find strong signal strength to increase the likelihood of the implementation of the program. For capacity building programs in columns (3) and (4), the estimation methods suggest that a strong signal has a weak and positive relationship with the implementation of the program. However, I do not find any relationship between these two dummies and capacity building programs for poor people. The result for village libraries in column (5) suggests that the likelihood of having the program is mostly driven by the presence of a strong signal. If the village has strong signal, it increases the probability of the village having a library by 0.8 percentage points. Finally, in column (6), the result for access to credit suggests that both strong and no signal affect the dependent variable. Villages with a strong signal have a 1 percentage point higher probability of having access to credit, and on the other hand, villages with no signal will have a 1.1 percentage point lower probability of having the program. In general, a strong signal has a positive relationship with the outcomes and no signal will reduce the likelihood of having the programs.

Because I construct the main explanatory variable from categorical data, I also test whether using the categorical data provides a similar result. Table A2 depicts the result that arises from using categorical signal strength. This variable will have value 2 if the signal is strong, 1 if the signal is weak and 0 if there is no signal strength. The first stage estimates a significant negative relationship between the instrument and the new categorical signal strength. The joint-F statistics of the Kleibergen-Paap test for weak identification is way above the minimum rule of thumb (F-statistics = 238).

The results suggest that categorical signal strength will increase the probability of having village rehabilitation programs, and both results are statistically significant at 1% (columns 1 - 2). Similar to the results obtained in Table 3, I do not find any evidence to demonstrate whether a categorical signal will affect the likelihood of a village having capacity building programs (columns 3 - 4). I also find that higher categorical signal strength is associated with higher likelihood of villages having libraries (column 5) and also access to credit (column 6). These results suggest that using an alternative explanatory variable does not change the baseline results and still provides robust causal evidence that mobile phone signal will affect some policies.

Finally, I also introduce a new dependent variable: a land conversion dummy. The variable is a dummy to establish whether there is a land conversion policy from agricultural land to non-agricultural land. The idea for this study comes from Besley et al. (2010), which posits that in a competitive political institution, government will move from agricultural sectors to non-agricultural sectors. This idea is also related to the structural transformation theory, in which there is a reallocation of economic activity from agricultural sectors to more advanced sectors. Table A3 depicts the estimation results for this analysis. It shows that in both LPM and 2SLS models, higher signal strength is associated with a higher probability of having land conversion from agricultural land to non-agricultural land, and is statistically significant at 1%.

Overall, the results of the outcomes are consistent with our hypothesis that there is a positive effect of mobile phone signal strength on outcomes. In the next section, I will explore some testable mechanisms that could explain why mobile phone signal could potentially affect some policies.

6 Mechanisms

In the previous section, I demonstrated that villages in Indonesia with strong mobile phone signal coverage will also have a higher probability of the implementation of certain policies. In this section I will try to disentangle the mechanisms which could explain why I observe this relationship. In general, there are four potential channels that could explain the results in this study: (1) That related to civic engagement or social participation. Mobile phone use will increase the likelihood of mutual and reciprocal assistance to maintain public goods conditions (*gotong royong*); (2) Mobile phone use also increases the political participation and makes villagers better informed, thus (3) Increasing accountability; and (4) Better mobile phone signal strength will increase the usage of telecommunication services, especially for people in rural areas.

Civic Engagement. For this analysis, a binary variable on whether the village has civic engagement activities (*gotong royong*) (e.g. mutual and reciprocal assistance (Bowen, 1986)) is the dependent variable. Civic engagement or collective action (I will use the terms interchangeably) in Indonesia are considered social activities that help others or that organise people to improve the conditions of their neighbourhood. *Gotong royong* has become a key element of Indonesian political and cultural systems. Indeed, this activity is very important in villages and rural areas, especially for agricultural and economic activities (Bowen, 1986). Therefore, higher civic engagement can be interpreted in two ways: (1) the villages have good community activities and social relationships, or (2) the villages lack necessary facilities and infrastructure or have just experienced a natural disaster, and therefore the people are working together to improve their current condition.

Higher social participation or civic engagement could be interpreted as ways to improve villages' conditions. To increase the probability of civic engagement, people need access to mobile phones. In the Indonesian context, mobile phone use is one of the channels to increase social participation. Unlike television, which reduces the probability of social activities (Olken, 2009), mobile phones provide a channel that encourages social participation. This could have a similar impact to the usage of mobile phones to increase political mobilisation.

Table 9 depicts the estimation results for civic engagement, where the dependent variable will have a value of 1 if a village exhibits civic engagement or *gotong royong* related activities, and 0 otherwise. Columns (1) to (2) present the results from the LPM method. Column (3) depicts the marginal effect for probit estimation, and column (4) shows the estimation results from the IV-2SLS method. All columns use village and year fixed effects (except column 3). We can observe that villages with higher signal strength have a higher probability of participating in civic engagement activities for all different specifications. The results are robust at the 1% for all columns. The estimated coefficient is 1.93 for the 2SLS-IV estimation method or 4.48 ($\approx 1.93/0.429$) relative to a standard deviation in civic engagement.

Overall, the results for civic engagement are quite different to those obtained in Olken (2009), which found that media (such as television and radio) reduce participation in social organisation in Indonesia. Thus, the results of the present study demonstrate that mobile phones can be an effective media tool to inform people about, or invite people to participate in, civic engagement activities. People can contact one another more easily when they need help or when they want to organise collective activities via mobile phones. This result is consistent with other studies on the positive association between mobile phone adoption and collective action or political mobilisation (Manacorda and Tesei, 2020; Shapiro and Weidmann, 2015; Pierskalla and Hollenbach, 2013), where mobile phone use has been found to act as a channel to improve policies through pressure or from social participation activities.

Table 9: Mechanism: Civic Engagement

	(1)	(2)	(3)	(4)
	Civic Engagement			
Signal strength	0.0095***	0.0076**	0.0070***	1.93***
	(0.0031)	(0.0033)	(0.0020)	(0.32)
N	163806	156506	156745	156506
R^2	0.571	0.582		
pseudo R^2			0.313	
Estimation Method	LPM	LPM	Probit	2SLS
Village FE	Yes	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Topography by Year FE	No	Yes	No	Yes
Controls	Yes	Yes	Yes	Yes
Flash rate intensity				-0.00058***
$\times$ time trend				(0.000087)
F				44.76
Stock-Yogo Critical Value				16.38

* Notes: Robust standard errors in parentheses and clustered at the village levels. The dependent variable in this estimation is a dummy variable for civic engagement activities at the village level. Column (3) is the marginal effect for probit regression. In column 4, signal strength is instrumented by mean annual flash rate density per km^2 between 1998 and 2013 at the village level interacting with a linear time trend. The F statistic for the first stage is the F-statistic of the Kleibergen-Paap rk Wald test for weak identification. See Table 2 and Table 6 for further information. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Villagers Political Participation. Another mechanism that could explain the impact of the introduction of mobile phones on policies is to see whether they increase villagers' political participation (e.g. voter turnout). Higher political participation or turnout is considered a good indicator of improved government performance. To analyse whether signal strength is associated with higher political participation, I use data from the *Indonesian Family Life Survey* (IFLS) – a longitudinal survey in Indonesia that represents around 83% of the Indonesian population. I use household data from IFLS 4 and IFLS 5, which were conducted in 2007 and 2014, respectively. In this data, there is no information about voter turnout during village elections, but the related information will be whether the villagers voted during the recent village elections. The dependent variable for this analysis will be 1 if the villagers voted for the village head via an election and 0 if otherwise. For this particular variable, I aggregated the data into the district levels and matched the data based on the districts to which the village belongs. Table 10 depicts the information for this analysis. I use district and year fixed effects because the variation that I have here for the dependent variable is at the level of the district to which the villages belong. I also include control variables in all specifications and topography by-year fixed effects in column (2).

From the table we can see that higher signal strength has a positive and robust effect on village elections. The IV-2SLS estimates that higher signal strength is associated with an increase in voting for the position of village head by 64 percentage points in column (1) where I do not include

Table 10: Mechanism: Village Election

	(1)	(2)
	Did you vote in the most recent village head election? (1 = Yes ; 0 = otherwise)	
Signal strength	0.64***	0.61***
	(0.18)	(0.17)
N	58420	58420
Estimation Method	2SLS	2SLS
District FE	Yes	Yes
Year FE	Yes	Yes
Topography by Year FE	No	Yes
Controls	Yes	Yes
Flash rate intensity	-0.00029***	-0.00029***
$\times$ time trend	(0.000076)	(0.000076)
F	14.48	14.76
Stock-Yogo Critival Value	13.84	13.84

* Notes: Robust standard errors in parentheses and clustered at the village levels. The sample in this table is individual who are living in *Desa*. The dependent variable is the aggregate variable from whether the respondent at village v in district d participated in the previous village election. The dependent variable is from Indonesian Family Life Survey (IFLS) rounds 4 and 5 in 2007 and 2014, respectively. Signal strength is instrumented by mean annual flash rate density per km^2 between 1998 and 2013 at the village level interacting with a linear time trend. The F statistic for the first stage is the F-statistic of the Kleibergen-Paap rk Wald test for weak identification. See Table 2 and table 6 for further information. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

topography by-year fixed effects. In column (2), including topography by-year fixed effects leads to a more precise point estimate, where the signal strength coefficient is around 0.61 with the standard error around 0.17. The first stage relationship between the instrument and signal strength still gives us a negative and statistically significant relationship. The F-statistics for this table are around 14.76, thus removing any concern about the potential weakness of the instrument.

This finding supports the previous mechanism where higher mobile phone use was found to increase village government accountability. The increasing level of political participation suggests that mobile phones influence voter turnout because they provide information for villagers. It is also supports the idea that the ability of villagers to access better information about leader performance may increase the incentives for the village head to perform well so as to avoid the villagers punishing them in the next set of elections.

Village Government Accountability. The next analysis is to see whether access to mobile phones will make villagers better informed about their leaders' performance and ultimately lead to better village government accountability. I expect that the presence of better signal strength will affect both villagers and the village head. For the villagers, it makes them better informed about their leader's performance. Better access to mobile phones due to better signals will make it easier for villagers to monitor their leaders. For village leaders, better signal strength will increase the pressure upon them to perform well, because they know that their people will be aware if they perform poorly or implement rent-seeking policies.

To address this question, I use data from the community-facility surveys from IFLS 4 and IFLS 5. Specifically, I use the information about villagers' perceptions of the relative quality of governance and absence of corruption in village government. I aggregate the community-level data into the sub-district levels so that I have the sub-districts-level average perception for these two variables.

For the variable concerned with villagers' perceptions of the quality of governance, I use a categorical variable with the value 4 if the respondents fell that compared to the previous survey the village governance is much better and 1 if it is much worse. For villagers' perception of corruption, the variable will have value 3 if the incidence of corruption becomes higher and 1 if it becomes lower. Table 11 illustrates the result of this analysis. In this table, I use 2SLS methods and control for village and year fixed effects as well as topography by-year fixed effects for all columns. Columns (1) and (2) provide the 2SLS estimates for perception of good governance and columns (3) and (4) depict the 2SLS estimates for perception of corruption.

First, we can infer that signal strength is associated with higher perception of good governance.

Table 11: Mechanism: Perception of Good Governance and Corruption

	(1)	(2)	(3)	(4)
	Perception of Good Governance 1 = much worst; 4 = much better		Perception of Corruption 1 = lower; 3 = higher	
Signal strength	2.55***	3.77***	-1.88**	-6.52
	(0.61)	(1.36)	(0.92)	(4.50)
N	29058	25850	25104	22206
Estimation Method	2SLS	2SLS	2SLS	2SLS
Village FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Topography by Year FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Flash rate intensity $\times$ time trend	-0.00057***	-0.00040***	-0.00036***	-0.00022
	(0.00013)	(0.00014)	(0.00013)	(0.00014)
F	19.25	8.16	7.15	2.22
Stock Yogo Critical Value	16.38	16.38	16.38	16.38

* Notes: Robust standard errors in parentheses and clustered at the village levels. The dependent variable in columns (1) and (2) is a categorical variable about villagers perception of community/village government good governance (1 = much worst and 4 = much better). The question in IFLS would be: "According to your opinion, comparing to [year], how is the governance in this village/township?". The dependent variable in columns (3) and (4) is a categorical variable about villagers perception of community/village government corruption. The question in IFLS would be: "Since [year], how was the incidence of corruption, collusion and nepotism in village government office changed?". The dependent variables are from Indonesian Family Life Survey (IFLS) rounds 4 and 5 in 2007 and 2014, respectively. Signal strength is instrumented by mean annual flash rate density per km^2 between 1998 and 2013 at the sub-district levels interacting with a linear time trend. The F statistic for the first stage is the F-statistic of the Kleibergen-Paap rk Wald test for weak identification. See Table 2 and Table 6 for further information. The unit observation here is at the village levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In column (1), the point estimate from regressing the dependent on signal strength without any covariates is around 2.55 and statistically significant at 1%. The result from the first stage in the same column also suggests that I still have a strong and negative association between signal strength and the instrument and I can reject the possibility that the first stage is weak. In column (2), by adding time varying covariates, the point estimate for signal strength becomes relatively higher and still significant at 1%. However, the F-statistics for the instrument in column (2) are barely below the minimum rule of thumb. Nonetheless, I still have a negative and robust relationship between the instrument and also signal strength. This is probably because I have a significantly lower number of observations, which reduces the sample size or power. Even so, we can still infer that higher mobile phone signal coverage will improve village government accountability.

Moving to villagers' perception of corruption, I expect that higher signal strength will reduce the incentives to engage in corrupt activities. The IV-2SLS estimation methods suggest that signal strength will indeed reduce the perception of corruption, and this is statistically significant at 5% in column (3). However the result becomes negative and statistically insignificant once I include covariates (See column 4). Although the results for villager perception on corruption are not robust for all specifications, we can still infer that access to mobile phones via better signal strength will reduce the probability of corruption. The findings for these two variables could be interpreted to indicate that village governments will perform better when they are being monitored by villagers. Again this finding supports the initial hypotheses that mobile phones will improve village government accountability through better governance while making village governments less corrupt.

Household Telecommunication Expenditure. The final testable mechanism will be the effect of signal strength on the usage of telecommunication services itself. Intuitively, higher signal strength will increase the usage of mobile phones and lead to an increase in spending for telecommunication consumption. However, there is no testable evidence to indicate whether higher usage of mobile phones will also increase the interaction with village leaders. The only possible evidence for this is anecdotal. For example, the previous governor of Jakarta provided his personal mobile phone number so the public could call him when they had issues. He received around 5,000 texts every week and addressed the issues by himself.[22] Another example is during the Obamacare vote in the US in which voters were encouraged to call their senator during the vote.[23] From this anecdotal evidence we can conjecture that access to mobile phones could easily become a channel to increase interaction with policy-makers, thus affecting policies.

Nonetheless, in this analysis I want to see whether people will use mobile phones when they are living in areas with higher signal strength. I use the data from IFLS 4 and 5 to answer this question, specifically using the household survey data. The dependent variable here is the log average household telecommunication expenditure at the level of the district to which the village belongs. Table 12 provides the IV-2SLS estimates for this analysis. All specifications are controlled by district and year fixed effects and time varying village characteristics. Topography by-year fixed effects are included in column (2).

The results from Table 12 indicate that households living in areas with higher signal strength spend more on telecommunication services. The results are positive and statistically significant at 1% for all different estimation methods. This result confirms that when villages have stronger coverage, people are incentivised to use mobile phones more than those who live in areas with weak coverage. The result from the first stage also suggests that we still have a negative and statistically significant relationship between the instrument and signal strength. The F-statistics for the first stage are around 14.12, which suggests there is no weak instrumental variable issue.

I also want to see whether people who are living in rural areas benefited more due to better signal strength. Previous studies have shown that poor people or people who are living in rural

[22]See https://www.thejakartapost.com/news/2014/08/04/jakarta-welcomes-first-ethnic-chinese-governor.html

[23]See https://edition.cnn.com/2017/02/03/politics/congress-phone-calls/index.html

Table 12: Mechanism: Effects on Household Telecommunication Expenditure

	(1) Log Communication Expenditure	(2) Log Communication Expenditure
Signal strength	11.5***	11.2***
	(3.11)	(3.01)
N	57853	57853
Estimation Method	2SLS	2SLS
District FE	Yes	Yes
Year FE	Yes	Yes
Topography by Year FE	No	Yes
Controls	Yes	Yes
Flash rate intensity	-0.00029***	-0.00029***
$\times$ time trend	(0.000077)	(0.000076)
F	14.12	14.25
Stock-Yogo Critical Value	13.84	13.84

* Notes: Robust standard errors in parentheses and clustered at the village levels. The dependent variable is log average household expenditures for telecommunication at village v in district d. The dependent variables are from Indonesian Family Life Survey (IFLS) rounds 4 and 5 in 2007 and 2014, respectively. Signal strength is instrumented by mean annual flash rate density per km^2 between 1998 and 2013 at the village level interacted by a time trend. The F statistic for the first stage is the F-statistic of the Kleibergen-Paap rk Wald test for weak identification. See Table 2 and Table 6 for further information. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

areas receive more benefit from the introduction of better ICT infrastructures. Table A4 provides the evidence for this analysis. Here, I divide the sample into rural villages (*desa*) in column (1) and urban villages (*kelurahan*) in column (2). I use the IV-2SLS estimation method for the analysis and it shows that households living in *desa* with higher signal strength will spend more on telecommunication. On the other hand, the result for *kelurahan* is statistically insignificant. This result confirms the previous studies, which have shown that the introduction of mobile phones will benefit people in rural areas more than people who are living in urban areas. But the insignificant result for *kelurahan* could also derive from the small sample that we have for this type of village, which gives us a less precise point estimate.

6.1 Mediation Analysis

Following Dippel et al. (2017) and Dippel et al. (2020), I also extend the mechanism exercise by decomposing the share of the treatment effect from the mediator variables. Table 13 provides the results for the mediation analysis. Panel A provides the total effect, direct effect, and indirect effect from the mediator on the policy or social development indicators in this study. Moreover Panel B depicts the effect from village elections. Panel C shows the mediator effect from good governance, and finally Panel D illustrates the effect of communication as the mediator in this study. We find that the first stage F-statistics and the second stage F-statistics for all mechanisms suggest that our mechanisms used in this study are able to explain the direct and indirect effects from the signal strength. As we can see the F-statistics value in all panels are substantially higher than 40.

In general, village rehabilitation for poor people, village libraries and credit for small enterprises can be explained by all the mediator variables. Although for village libraries, the effect of communication is statistically insignificant. In terms of the size of the mediator effect on our outcomes, we can see that the indirect effect plays a significant role on the dependent variables. For example, civic engagement could explain almost 98.9% ($\approx 1.281/1.286 * 100$; Column 1 panel A) and 99.6% ($\approx 1.166/1.179 * 100$; Column 2 Panel A) of the impact on the village rehabilitation and village rehabilitation for poor people. The indirect effects from civic engagement are also statistically significant at the 1% level.

Village election turns to play a significant role in mediating the impact of signal on outcome variables. The indirect effects, or the effect of village election as the mediator is approximately around 81.7% for village rehabilitation program for the poor (in Column 2 Panel B), 91.4% for village libraries (in Column 5 Panel B), and 85.5% for credit for small enterprises (in Column 6 Panel B). All indirect effects are statistically significant at the 1%.

In panel C, good governance also influences the impact of signal strength on the outcome indicators. It has a statistically significant indirect effects in columns (2), (5), and (6), with the percentage of its effects are around 81%, 90%, and 87%, respectively. Finally in Panel D, spending for telecommunication slightly explained the impact of mobile phones signal on several outcomes. It only affects village rehabilitation for poor people and credit for small enterprises, although it is statistically significant at the 5%.

To sum, all the mechanism proposed in this study plays an important role in explaining the impact of signal on policies. Although the role of civic engagement and village elections are more substantial compared to good governance and telecommunication expenditure.

Table 13: Mediation Analysis Following Dippel et al. (2017) and Dippel et al. (2020)

	(1) Village Rehab.	(2) Village Rehab. for Poor People	(3) Capacity Building	(4) Capacity Build. for Poor People	(5) Village Lib.	(6) Credit for Small Enterp.
			Panel A Civic Engagement			
Total Effect	1.286***	1.179***	-0.082	-0.085	0.400***	0.601***
	(0.0040)	(0.002)	(0.140)	(0.060)	(0.142)	(0.033)
Direct Effect	0.004	0.012***	0.014***	0.002***	0.016***	0.033***
	(0.003)	(0.002)	(0.002)	(0.0008)	(0..001)	(0.002)
Indirect Effect	1.281***	1.166***	-0.097	-0.088	0.384**	0.568***
	(0.306)	(0.255)	(0.140)	(0.061)	(0.148)	(0.184)
1^{st} Stage F-stat	225	225	225	225	225	225
2^{nd} Stage F-stat	1891	1891	1891	1891	1891	1891
N	156745	156745	156745	156745	156745	156745
			Panel B Village Election			
Total Effect	0.339	1.156***	0.404**	-0.136*	0.736***	0.693***
	(0.209)	(0.240)	(0.185)	(0.075)	(0.198)	(0.211)
Direct Effect	0.007	0.005	0.008**	0.002*	0.011***	0.034***
	(0.005)	(0.004)	(0.004)	(0.001)	(0.003)	(0.004)
Indirect Effect	0.309	0.945***	0.410**	-0.123*	0.673***	0.586***
	(0.208)	(0.236)	(0.189)	(0.073)	(0.206)	(0.213)
1^{st} Stage F-stat	225	225	225	225	225	225
2^{nd} Stage F-stat	73	73	73	73	73	73
N	58420	58420	58420	58420	58420	58420
			Panel C Good Governance			
Total Effect	0.191	0.870***	0.204	-0.061	0.415***	0.510***
	(0.155)	(0.157)	(0.141)	(0.059)	(0.135)	(0.154)
Direct Effect	0.002	-0.002	0.0009	0.003	0.010*	0.025***
	(0.007)	(0.006)	(0.006)	(0.002)	(0.005)	(0.007)
Indirect Effect	0.224	0.703***	0.241	-0.056	0.375***	0.444***
	(0.156)	(0.162)	(0.141)	(0.057)	(0.139)	(0.158)
1^{st} Stage F-stat	225	225	225	225	225	225
2^{nd} Stage F-stat	125	125	125	125	125	125
N	35681	35681	35681	35681	35681	35681
			Panel D Communication Expenditure			
Total Effect	0.436	0.807***	0.112	-0.147	0.149	0.869***
	(0.272)	(0.240)	(0.220)	(0.093)	(0.214)	(0.284)
Direct Effect	-0.006	0.032**	-0.012	-0.002	0.045***	0.063***
	(0.016)	(0.012)	(0.013)	(0.006)	(0.009)	(0.015)
Indirect Effect	0.439	0.753**	0.118	-0.145	0.099	0.808**
	(0.291)	(0.306)	(0.222)	(0.100)	(0.214)	(0.351)
1^{st} Stage F-stat	225	225	225	225	225	225
2^{nd} Stage F-stat	47	47	47	47	47	47
N	7793	7793	7793	7793	7793	7793
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Topography by Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

* Notes: Robust standard errors in parentheses and clustered at the village levels. Time varying covariates in this table are the same with covariates used in Table 2. Village FE are included in Panel A and C. District FE are included in Panel B and D. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7 Conclusions

This study explores the village-level data from three waves of Indonesia's village census to investigate the role of mobile phones in policy-making. I find that increased signal strength is associated with village rehabilitation programs, especially for poor people. I also find that a stronger mobile phone signal will increase the likelihood of villages having libraries and access to credit for small enterprises. The results are robust after implementing various estimation strategies.

To acknowledge the potential bias caused by several endogeneity problems, I performed instrumental variable estimations, using lightning strike intensity as the instrument for assessing signal strength. The results from the 2SLS support the results from the LPM and probit estimation methods, even though the 2SLS results yield a higher magnitude to the other methods. Nevertheless, the results from the 2SLS reveal that mobile phone signal strength has a causal relationship with a village leader's policies.

I also extended the analysis by splitting the sample into rural villages (*desa*) and urban villages (*kelurahan*). The results indicate that there is a heterogeneous effect between urban and rural villages. The results for *kelurahan* are statistically insignificant. This is likely because there is a significant difference in terms of the government characteristics between urban and rural villages. Whereas village leaders in *kelurahan* are appointed by the district government, and most of them are civil servants, village leaders in *desa* are elected through village elections and have greater power than village leaders in *kelurahan*.

There are several channels that might explain why mobile phones will affect policies. First, I argue that civic engagement and social participation will increase due to higher signal strength and ultimately exert pressure for the leaders to perform well. Second, I show that villages with higher signal strength will have higher political participation in village elections. Third, village heads in villages with stronger mobile phones signals will be more accountable and less corrupt. Finally, higher signal strength will increase the usage of mobile phones for the purpose of interacting directly with leaders.

These findings could be useful to enhance the role of mobile phones in policy-making throughout the world. Some policy recommendations for Indonesia would be to increase access to ICT infrastructure in the country by expanding ICT availability, especially in remote areas. This can also be implemented in other countries, as many areas throughout the world still lack investment in ICT infrastructure. This study also contributes to our understanding of the role of mobile phones on leaders' performance and policy choices.

Although this study argued that lightning strike poses as a good instrumental variable, but issues with the instrument validity need to be acknowledged and become the avenue for future studies. Alternative instrumental variable that may isolate the endogeneity problem from the independent variable may help future studies in this area. Other than alternative instrumental variables, this study suggests a number of potentially fruitful areas of analysis that could be pursued in the future. First, using alternative ICT data could potentially enhance the robustness of the results; for example, data on ICTs before the expansion of ICT infrastructure in Indonesia. Aggregating data to the district level could also help explain the impact of mobile phones on district governments, since these governments have a greater responsibility to provide service delivery. Additionally, information related to the types of interaction between villagers and their leaders would help to identify the types of communication that could lead to better policies and accountability. Finally, due to the growth of social media in the past decade, it would be useful to analyse the impact of digital media (e.g. smart phones, tablets and government monitoring app) and social media (e.g. Twitter and Facebook) on policies.

References

Aker, J. C. (2010). Information from markets near and far: Mobile phones and agricultural markets in Niger. *American Economic Journal: Applied Economics*, 2(3):46–59.

Aker, J. C., Collier, P., and Vicente, P. C. (2017). Is information power? using mobile phones and free newspapers during an election in Mozambique. *Review of Economics and Statistics*, 99(2):185–200.

Aker, J. C. and Fafchamps, M. (2014). Mobile phone coverage and producer markets: Evidence from West Africa. *The World Bank Economic Review*, 29(2):262–292.

Aker, J. C. and Mbiti, I. M. (2010). Mobile phones and economic development in Africa. *The Journal of Economic Perspectives*, 24(3):207–232.

Albrecht, R., Goodman, S., Petersen, W., Buechler, D., Bruning, E., Blakeslee, R., and Christian, H. (2011). The 13 years of trmm lightning imaging sensor: from individual flash characteristics to decadal tendencies.

Andersen, T. B., Bentzen, J., Dalgaard, C.-J., and Selaya, P. (2011). Does the internet reduce corruption? evidence from US states and across countries. *The World Bank Economic Review*, 25(3):387–417.

Andersen, T. B., Bentzen, J., Dalgaard, C.-J., and Selaya, P. (2012). Lightning, it diffusion, and economic growth across US states. *Review of Economics and Statistics*, 94(4):903–924.

Angrist, J. D. (1998). Estimating the labor market impact of voluntary military service using social security data on military applicants. *Econometrica*, 66(2):249–288.

Angrist, J. D. and Imbens, G. W. (1995). Two-stage least squares estimation of average causal effects in models with variable treatment intensity. *Journal of the American Statistical Association*, 90(430):431–442.

Angrist, J. D. and Krueger, A. B. (2001). Instrumental variables and the search for identification: From supply and demand to natural experiments. *Journal of Economic Perspectives*, 15(4):69–85.

Angrist, J. D. and Pischke, J. (2009). *Mostly Harmless Econometrics: An Empiricist Companion*. Princeton University Press, Princeton.

Antlöv, H. (2003). Village government and rural development in Indonesia: The new democratic framework. *Bulletin of Indonesian Economic Studies*, 39(2):193–214.

Antlöv, H., Wetterberg, A., and Dharmawan, L. (2016). Village governance, community life, and the 2014 village law in Indonesia. *Bulletin of Indonesian Economic Studies*, 52(2):161–183.

Bailard, C. S. (2009). Mobile phone diffusion and corruption in Africa. *Political Communication*, 26(3):333–353.

Baulch, E. (2017). Mobile phones: advertising, consumerism and class. In Jurriëns, E. and Tapsell, R., editors, *Digital Indonesia: Connectivity and Divergence*. ISEAS-Yusof Ishak Institute.

Bebbington, A., Dharmawan, L., Fahmi, E., and Guggenheim, S. (2006). Local capacity, village governance, and the political economy of rural development in Indonesia. *World Development*, 34(11):1958–1976.

Besley, T. and Burgess, R. (2002). The political economy of government responsiveness: Theory and evidence from India. *The Quarterly Journal of Economics*, 117(4):1415–1451.

Besley, T., Persson, T., and Sturm, D. M. (2010). Political competition, policy and growth: Theory and evidence from the US. *Review of Economic Studies*, 77:1329–1352.

Bowen, J. R. (1986). On the political construction of tradition: Gotong royong in Indonesia. *The Journal of Asian Studies*, 45(3):545–561.

Buys, P., Dasgupta, S., Thomas, T. S., and Wheeler, D. (2009). Determinants of a digital divide in Sub-Saharan Africa: A spatial econometric analysis of cell phone coverage. *World Development*, 37(9):1494–1505.

Cecil, D. J., Buechler, D. E., and Blakeslee, R. J. (2014). Gridded lightning climatology from TRMM-LIS and OTD: Dataset description. *Atmospheric Research*, 135:404–414.

Central Bureau of Statistics (2014). Indonesia village cencus/*Potensi Desa*.

Cook, F. L., Tyler, T. R., Goetz, E. G., Gordon, M. T., Protess, D., Leff, D. R., and Molotch, H. L. (1983). Media and agenda setting: Effects on the public, interest group leaders, policy makers, and policy. *Public Opinion Quarterly*, 47(1):16–35.

Devarajan, S., Khemani, S., and Walton, M. (2011). *Civil society, public action and accountability in Africa*. The World Bank.

Dippel, C., Ferrara, A., and Heblich, S. (2020). Causal mediation analysis in instrumental-variables regressions. *The Stata Journal*, 20(3):613–626.

Dippel, C., Gold, R., Heblich, S., and Pinto, R. (2017). Instrumental variables and causal mechanisms: Unpacking the effect of trade on workers and voters. Technical report, National Bureau of Economic Research.

Enikolopov, R. and Petrova, M. (2015). Media capture: empirical evidence. In *Handbook of media Economics*, volume 1, pages 687–700. Elsevier.

Enikolopov, R., Petrova, M., and Zhuravskaya, E. (2011). Media and political persuasion: Evidence from Russia. *The American Economic Review*, 101(7):3253–3285.

Evers, P. J. (2000). Resourceful villagers, powerless communities: Rural village government in Indonesia. mimeo, Jakarta, World Bank.

Ferraz, C. and Finan, F. (2008). Exposing corrupt politicians: the effects of brazil's publicly released audits on electoral outcomes. *The Quarterly Journal of Economics*, 123(2):703–745.

Ferraz, C. and Finnan, F. (2011). Electoral accountability and corruption: Evidence from the audit reports of local governments. *American Economic Review*, 101(4):1274–1311.

Gentzkow, M. (2006). Television and voter turnout. *The Quarterly Journal of Economics*, 121(3):931–972.

Gentzkow, M., Shapiro, J. M., and Sinkinson, M. (2011). The effect of newspaper entry and exit on electoral politics. *The American Economic Review*, 101(7):2980–3018.

Greene, W. (2004). The behaviour of the maximum likelihood estimator of limited dependent variable models in the presence of fixed effects. *The Econometrics Journal*, 7(1):98–119.

Grossman, G., Humphreys, M., and Sacramone-Lutz, G. (2014). "i wld like u WMP to extend electricity 2 our village": On information technology and interest articulation. *American Political Science Review*, 108(3):688–705.

Grossman, G., Michelitch, K., and Santamaria, M. (2017). Texting complaints to politicians: Name personalization and politicians' encouragement in citizen mobilization. *Comparative Political Studies*, 50(10):1325–1357.

Hausman, J. (2001). Mismeasured variables in econometric analysis: problems from the right and problems from the left. *Journal of Economic Perspectives*, 15(4):57–67.

Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica*, 47(1):153–161.

Jensen, R. (2007). The digital provide: Information (technology), market performance, and welfare in the South Indian fisheries sector. *The Quarterly Journal of Economics*, 122(3):879–924.

Lee, R. C. and Findlay, C. (2005). Telecommunications reform in Indonesia: Achievements and challenges. *Bulletin of Indonesian Economic Studies*, 41(3):341–365.

Lewis, B. D. (2015). Decentralising to villages in Indonesia: Money (and other) mistakes. *Public Administration and Development*, 35(5):347–359.

Manacorda, M. and Tesei, A. (2020). Liberation technology: Mobile phones and political mobilization in africa. *Econometrica*, 88(2):533–567.

Marler, W. (2018). Mobile phones and inequality: Findings, trends, and future directions. *New Media & Society*, 20(9):3498–3520.

Martinez-Bravo, M. (2014). The role of local officials in new democracies: Evidence from Indonesia. *The American Economic Review*, 104(4):1244–1287.

Martinez-Bravo, M. (2017). *American Economic Journal: Applied Economics*, 9(2):256–89.

Ministry of Home Office (2014). Pembentukan daerah-daerah otonom di Indonesia sampai dengan tahun 2014.

Minnesota Population Center (2017). Integrated public use microdata series, international: Version 6.5 [dataset]. Minneapolis: University of Minnesota. http://doi.org/10.18128/D020.V6.5.

OECD (2018). *SME and Entrepreneurship Policy in Indonesia 2018*.

Olken, B. A. (2007). Monitoring corruption: evidence from a field experiment in indonesia. *Journal of political Economy*, 115(2):200–249.

Olken, B. A. (2009). Do television and radio destroy social capital? evidence from Indonesian villages. *American Economic Journal: Applied Economics*, 1(4):1–33.

Pande, R. (2011). Can informed voters enforce better governance? experiments in low-income democracies. *Annu. Rev. Econ.*, 3(1):215–237.

Persson, T. and Tabellini, G. (2000). *Political Economics: Explaining Economic Policy*. MIT Press, Cambridge.

Pierskalla, J. H. and Hollenbach, F. M. (2013). Technology and collective action: The effect of cell phone coverage on political violence in Africa. *American Political Science Review*, 107(2):207–224.

PT Telekomunikasi Selular (2016). Building Indonesia digital economy, 2016 annual report.

Reinikka, R. and Svensson, J. (2011). The power of information in public services: Evidence from education in Uganda. *Journal of Public Economics*, 95(7):956–966.

Rezki, J. F. (2022). Political competition and economic performance: evidence from indonesia. *Economics of Governance*, pages 1–32.

Rohman, I. K. (2014). Review of Indonesian broadband development. Technical report, LIRNEasia.

Rohman, I. K. and Bohlin, E. (2014). Decomposition analysis of the telecommunications sector in indonesia: what does the cellular era shed light on? *Telecommunications Policy*, 38(3):248–263.

Shapiro, J. N. and Weidmann, N. B. (2015). Is the phone mightier than the sword? cellphones and insurgent violence in Iraq. *International Organization*, 69(2):247–274.

Snyder Jr, J. M. and Strömberg, D. (2010). Press coverage and political accountability. *Journal of Political Economy*, 118(2):355–408.

Staiger, D. and Stock, J. H. (1997). Instrumental variables regression with weak instruments. *Econometrica*, 65:557–586.

Strömberg, D. (2001). Mass media and public policy. *European Economic Review*, 45(4):652–663.

Strömberg, D. (2004a). Mass media competition, political competition, and public policy. *The Review of Economic Studies*, 71(1):265–284.

Strömberg, D. (2004b). Radio's impact on public spending. *The Quarterly Journal of Economics*, 119(1):189–221.

The World Bank (2016). World development report 2016: Digital dividends.

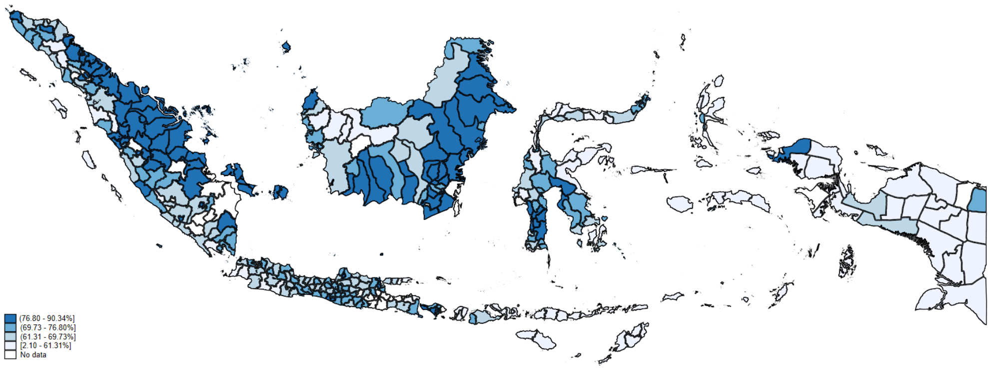
Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT press.

Yanagizawa-Drott, D. (2014). Propaganda and conflict: Evidence from the rwandan genocide. *The Quarterly Journal of Economics*, 129(4):1947–1994.

Yudhistira, M. H., Khairina, N., Dartanto, T., and Nuryakin, C. (2021). Information technology and local conflict: evidence from indonesia. *Conflict, Security & Development*, 21(6):831–848.

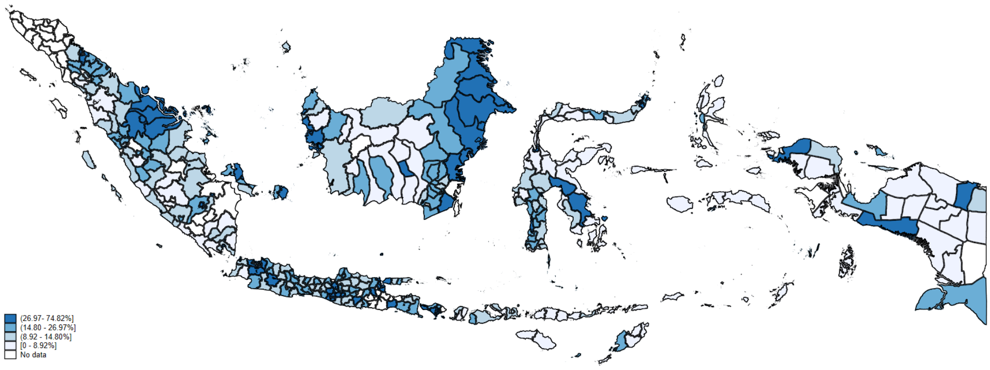
Appendix A Figures and Tables

Figure A1: Mobile Phone Subscriptions at District Level in 2010



Source: Author's calculation from Population Census 2010

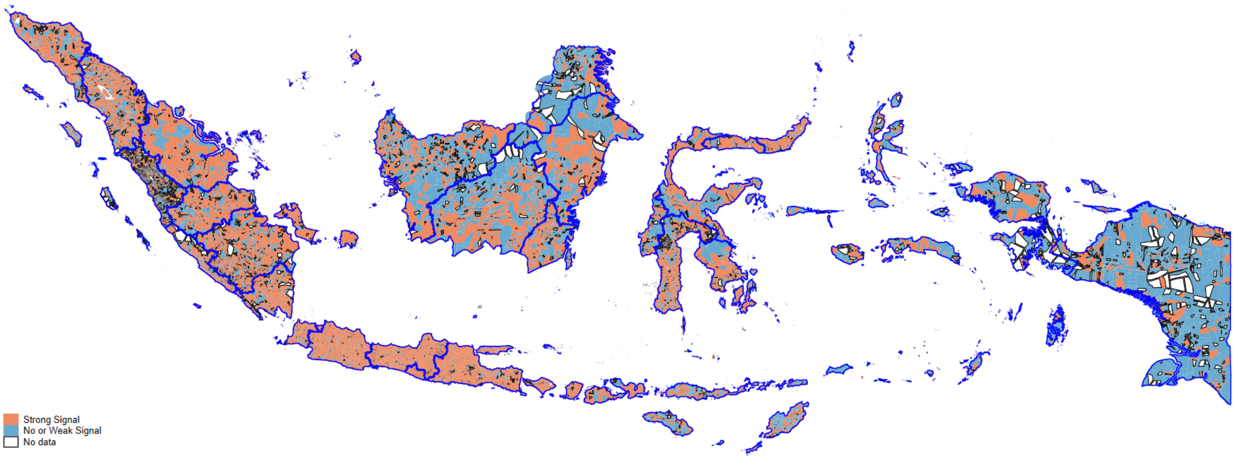
Figure A2: Mobile Phone Subscriptions at District Level in 2005



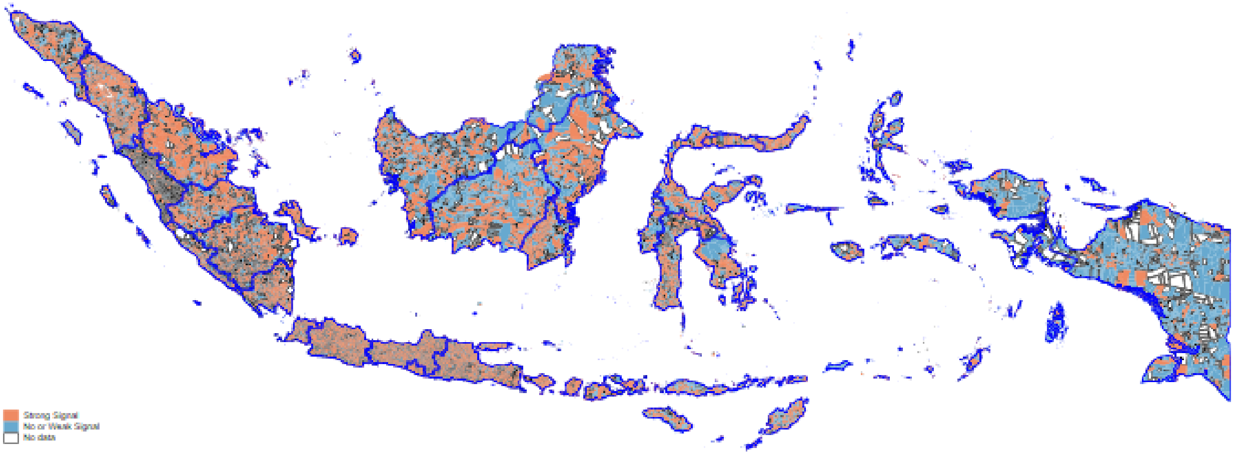
Source: Author's calculation from SUPAS 2005

Figure A3: Mobile Phone Signal Strength at Village Level between 2008 and 2014

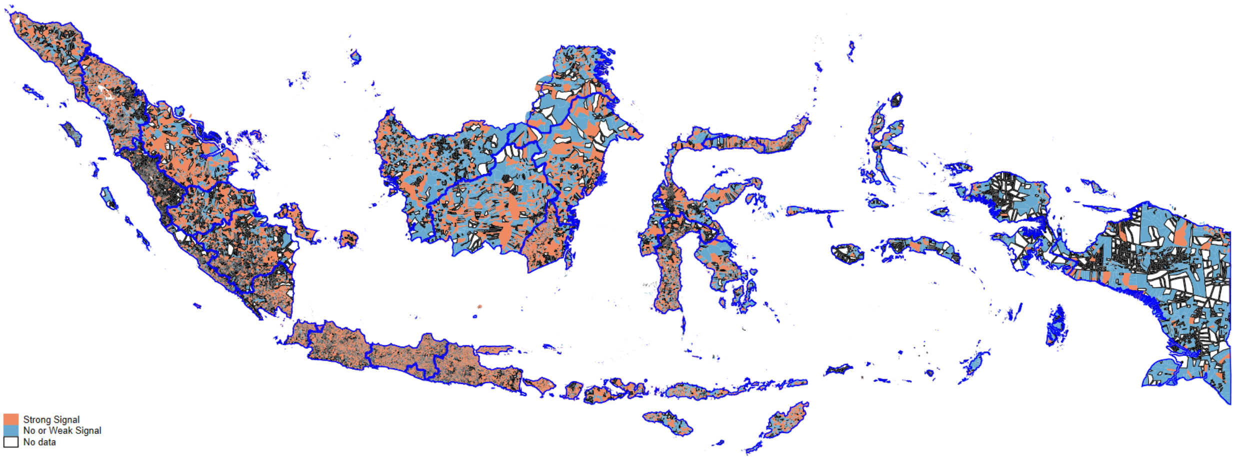
Panel A: Podes 2014



Panel B: Podes 2011



Panel C: Podes 2008



Source: Author's calculation from Podes 2014, 2011 and 2008

Table A1: Reduced Form

	(1) Village Rehabilitation	(2) Village Rehabilitation for Poor People	(3) Capacity Building	(4) Capacity Building for Poor People	(5) Village Libraries	(6) Credit for Small Enterprises
Flash Rate Intensity	-0.00090***	-0.00073***	-0.0000062	0.000064	-0.00029***	-0.00025***
× time trend	(0.00011)	(0.000085)	(0.000091)	(0.000040)	(0.000079)	(0.000095)
N	156745	156745	156745	156745	156745	156745
R^2	0.138	0.042	0.013	0.003	0.014	0.006
Estimation Method	OLS	OLS	OLS	OLS	OLS	OLS
Village FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Topography by Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

* Notes: Robust standard errors in parentheses and clustered at the village levels. The years included in the regressions are 2008, 2011 and 2014. See Table 2 and Table 6 for further information. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Robustness: Alternative Explanatory Variable

	(1) Village Rehabilitation	(2) Village Rehabilitation for Poor People	(3) Capacity Building	(4) Capacity Building for Poor People	(5) Village Libraries	(6) Credit for Small Enterprises
Categorical signal	0.54***	0.45***	0.015	-0.034	0.15***	0.13**
	(0.074)	(0.056)	(0.053)	(0.023)	(0.047)	(0.055)
N	156506	156506	156506	156506	156506	156506
Estimation Method	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Village FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Topography by Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Flash rate intensity	-0.0017***	-0.0017***	-0.0017***	-0.0017***	-0.0017***	-0.0017***
× time trend	(0.00011)	(0.00011)	(0.00011)	(0.00011)	(0.00011)	(0.00011)
F	238.27	238.27	238.27	238.27	238.27	238.27

* Notes: Robust standard errors in parentheses and clustered at the village levels. The years included in the regressions are 2008, 2011 and 2014. Categorical signal strength equals to 2 if signal strength is strong, 1 if signal strength is weak and 0 if there is no signal. Categorical signal strength is instrumented by mean annual flash rate density per km^2 between 1998 and 2013 at the village level interacted by a time trend. The F statistic for the first stage is the F-statistic of the Kleibergen-Paap rk Wald test for weak identification. See Table 2 and Table 6 for further information. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Effects on Land Conversion

	(1)	(2)
	Land Conversion from Agri. to Non-agri. Land	
Signal strength	0.012***	1.06***
	(0.0034)	(0.23)
N	156506	156506
R^2	0.493	
Estimation Method	LPM	2SLS
Village FE	Yes	Yes
Year FE	Yes	Yes
Topography by Year FE	Yes	Yes
Controls	Yes	Yes
Flash rate intensity × time trend		-0.00058***
		(0.000087)
F		44.76

* Notes: Robust standard errors in parentheses and clustered at the village levels. The dependent variable is dummy for land conversion from agricultural land to non-agricultural land. Signal strength is instrumented by mean annual flash rate density per km^2 between 1998 and 2013 at the village level interacted by a time trend. The F statistic for the first stage is the F-statistic of the Kleibergen-Paap rk Wald test for weak identification. See Table 2 and Table 6 for further information. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Effects on Household Telecommunication Expenditure: Desa versus Kelurahan

	(1)	(2)
	Log Communication Expenditure	
Signal strength	8.71***	-444.5
	(2.74)	(3361.8)
N	49681	8140
Estimation Method	2SLS	2SLS
District FE	Yes	Yes
Year FE	Yes	Yes
Topography by Year FE	Yes	Yes
Controls	Yes	Yes
Sample	Desa	Kelurahan
Flash rate intensity × time trend	-0.00030***	0.000013
	(0.000091)	(0.000098)
F	10.63	0.017

* Notes: Robust standard errors in parentheses and clustered at the village levels. The dependent variable is log average household expenditures for telecommunication at village v in district d. The dependent variables are from Indonesian Family Life Survey (IFLS) rounds 4 and 5 in 2007 and 2014, respectively. Signal strength is instrumented by mean annual flash rate density per km^2 between 1998 and 2013 at the village level interacted by a time trend. The F statistic for the first stage is the F-statistic of the Kleibergen-Paap rk Wald test for weak identification. See Table 2 and Table 6 for further information. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Additional Results: Random Number < 0.5 versus Random Number > 0.5

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Village Rehabilitation		Village Rehabilitation for Poor People		Capacity Building		Capacity Building for Poor People		Village Libraries		Credit for Small Enterprises	
Signal strength	1.70***	1.37**	1.59***	1.18**	-0.15	0.066	-0.057	-0.20	0.61**	0.28	0.55*	0.72*
	(0.58)	(0.59)	(0.49)	(0.46)	(0.25)	(0.29)	(0.11)	(0.13)	(0.28)	(0.28)	(0.30)	(0.38)
N	78231	78392	78231	78392	78231	78392	78231	78392	78231	78392	78231	78392
Estimation method	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Sub-district FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Topography by Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Lower Half	Upper Half	Lower Half	Upper Half	Lower Half	Upper Half	Lower Half	Upper Half	Lower Half	Upper Half	Lower Half	Upper Half
First stage												
Flash rate intensity	-0.000344***	-0.000291***	-0.000344***	-0.000291***	-0.000344***	-0.000291***	-0.000344***	-0.000291***	-0.000344***	-0.000291***	-0.000344***	-0.000291***
$\times$ time trend	(0.000096)	(0.000097)	(0.000096)	(0.000097)	(0.000096)	(0.000097)	(0.000096)	(0.000097)	(0.000096)	(0.000097)	(0.000096)	(0.000097)
F	12.8	8.94	12.8	8.94	12.8	8.94	12.8	8.94	12.8	8.94	12.8	8.94

* Notes: Robust standard errors in parentheses and clustered at the village levels. The dependent variables in this estimation are dummy variable for village rehabilitation program at the village level (columns 1 - 2), dummy variable for village rehabilitation programs where the beneficiaries are only poor people (columns 3 - 4) dummy variable for village capacity building program at the village level (columns 5 - 6); dummy variable for village capacity building programs where the beneficiaries are only poor people (columns 7 - 8); dummy variable for village libraries (columns 9 - 10) and dummy variable for credit for small enterprises (columns 11 - 12). The F statistic for the first stage is the F-statistic of the Kleibergen-Paap rk Wald test for weak identification. See Table 2 and Table 6 for further information. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6: Additional Results: Strong versus Weak Signal

	(1)	(2)	(3)	(4)	(5)	(6)
	Village Rehabilitation	Village Rehabilitation for Poor People	Capacity Building	Capacity Building for Poor People	Village Libraries	Credit for Small Enterprises
Strong signal strength	0.027***	0.039***	-0.0088**	-0.00069	0.0023	0.031***
	(0.0070)	(0.0050)	(0.0043)	(0.0019)	(0.0033)	(0.0042)
Weak strength	0.025***	0.030***	-0.013***	-0.00085	-0.0047	0.018***
	(0.0067)	(0.0048)	(0.0039)	(0.0017)	(0.0030)	(0.0038)
N	156506	156506	156506	156506	156506	156506
R^2	0.480	0.403	0.445	0.368	0.512	0.501
Estimation method	LPM	LPM	LPM	LPM	LPM	LPM
Village FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
District by Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Topography by Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

* Notes: Robust standard errors in parentheses and clustered at the village levels. The years included in the regressions are 2008, 2011 and 2014. Strong signal strength will be equal to 1 if signal strength is strong and 0 if otherwise. No signal strength will be equal to 1 if there is no signal and 0 if otherwise. Time varying covariates in this table are the same with covariates used in Table 2. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix B Not for Publication

Table B1: Additional Results: Java versus Non-Java

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Village Rehabilitation		Village Rehabilitation for Poor People		Capacity Building		Capacity Building for Poor People		Village Libraries		Credit for Small Enterprises	
Signal strength	-0.069	31.7	1.36	6.67	4.12*	3.33	0.43	-0.93	1.69	-0.93	2.76*	-0.50
	(0.71)	(112.9)	(0.86)	(23.8)	(2.20)	(12.0)	(0.35)	(3.43)	(1.05)	(4.05)	(1.54)	(3.13)
N	43233	113512	43233	113512	43233	113512	43233	113512	43233	113512	43233	113512
Estimation method	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Sub-district FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Topography by Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Java	Non-Java	Java	Non-Java	Java	Non-Java	Java	Non-Java	Java	Non-Java	Java	Non-Java
First stage												
Flash rate intensity	-0.000187*	-0.000027	-0.000187*	-0.000027	-0.000187*	-0.000027	-0.000187*	-0.000027	-0.000187*	-0.000027	-0.000187*	-0.000027
$\times$ time trend	(0.000096)	(0.000095)	(0.000096)	(0.000095)	(0.000096)	(0.000095)	(0.000096)	(0.000095)	(0.000096)	(0.000095)	(0.000096)	(0.000095)
F	3.81	0.08	3.81	0.08	3.81	0.08	3.81	0.08	3.81	0.08	3.81	0.08

[*] Notes: Robust standard errors in parentheses and clustered at the village levels. The dependent variables in this estimation are dummy variable for village rehabilitation program at the village level (columns 1 - 2), dummy variable for village rehabilitation programs where the beneficiaries are only poor people (columns 3 - 4) dummy variable for village capacity building program at the village level (columns 5 - 6); dummy variable for village capacity building programs where the beneficiaries are only poor people (columns 7 - 8); dummy variable for village libraries (columns 9 - 10) and dummy variable for credit for small enterprises (columns 11 - 12). The F statistic for the first stage is the F-statistic of the Kleibergen-Paap rk Wald test for weak identification. See Table 2 and Table 6 for further information. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$