The Implications of Technology Policy on Inequality: Evidence from Thailand

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Abstract

This study aims to evaluate the impact of technology policy on inequality in different aspects: labour force, education and healthcare. The Thai government has been driving the country with ICT policies since 2001 to provide Thai people with a better quality of life and create equal opportunities. The difference-in-differences approach is applied to examine the intervention using the Socioeconomic survey (SES) assembled by the National Statistical Office of Thailand (NSO). For household-level analysis, the results show that ICT policies seem to contribute to higher earnings, especially among economically strong households. In addition, they have encouraged education by increasing educational attainment and reducing educational costs. Meanwhile, healthcare spending tends to expand. Analysing the aggregate data at the province level by calculating the inequality with the Gini coefficient, the results provide evidence that ICT policies can reduce income inequality and educational disparity (measured by years of schooling) but increase the disparities in expenditure in both education and healthcare. Therefore, policymakers should propose some solutions to the persisting expenditure inequality. There is also a gap between households regarding differences in areas, ICT usage patterns and occupations in each economic sector that must be addressed.

Keywords: Technology policy, Inequality, Difference-in-Differences, Thailand

1 Introduction

Technological change is the first appearance in a new local production, process, or product that is considered the result of an endogenous process (Evenson and Westphal, 1995). Technological change is a loose concept that has many meanings. This idea was based on issues of unemployment, as well as the relationship between management and labour in the 1930s, which was later applied to the study of economic growth. Technological changes are quantified by measuring the productivity of labour, capital, and other inputs (Godin, 2015). The overall pattern of technical change is one of coevolution, which is the evolution of mutual adaptation in complex systems by supporting the growth rate optimization and innovation of technology (Rip and Kemp, 1997; Coccia, M., 2019).

Technology raises the demand for skills, namely skill-biased technological change (SBTC), which is the increasing need for educated and skilled workers as new technologies enter the workplace. New technologies, especially information and communication technology (ICT), enable skilled workers to work more efficiently (Van Reenen, 2011). On the other hand, ICT replaces unskilled workers, e.g., robotic equipment replacing assembly line workers. In general, higher-educated workers can better cope with how these new ideas should be best applied in the new technology era.

Regarding policy issues, public policy plays a crucial role in encouraging people to embrace new technology. New technologies are only used when a driving force is behind them, better known as "Technology-push" (Rothwell and Wissema, 1986). To understand this "Technology-push" model, one needs to go back at least to Schumpeter's early work, where he demonstrated a model of the life cycle of technological change in terms of a three-stage development process, including the phases of invention, innovation, and diffusion (Christiansen, 2001). It is sufficient to present a national policy to ensure the adoption of economically guaranteed technology in the early stages and proper diffusion through the economy. Therefore, the necessary policy is to achieve effective resource allocation in the context of externally defined technological options.

Governments should provide incentives and facilitate technological development in developing the country's technological infrastructure. Developing countries need to be made aware that rapid economic growth is only possible with significant technological developments. Governments have two roles in technology development: one is to provide a policy environment suitable for the private sector in technology investment; the other is to be an investor in areas where the private sector cannot operate effectively for the benefit of the public. The public investment includes expenditures on research and development, technology dissemination, and support for training and related activities (Evenson and Westphal, 1995).

Information technology is essential and considered a universal phenomenon of the 21st century since the global spread of internet technology. Such technology has influenced over policymaking of countries around the world, e.g., the concept of National Information Infrastructure (NII) and the Information Superhighway of the United States (Hura, 1998). The information revolution is bringing people from different backgrounds to the information superhighway, with the internet as a global platform connecting thousands of networks. A vast amount of information is available on the internet for users, and it also provides forums for users to share information resources. The NII has a profound impact on the way people work, learn, live, and communicate. In short, when utilized wisely, technology can strengthen the national economy, increase competitiveness, and improve people's quality of life. That is why public policies in this regard play a vital role (Kalil, 1995).

Today, it is inevitable that the world of work and life is undergoing a tremendous transformation with newly emerging economies. Work is transformed due to technological innovation, especially computer technology and ICT, which are rapidly evolving. These disruptive technologies have the potential to increase productivity in various industries. In developing countries, ICT and its applications are exceedingly contributing to public services such as health, education and economic opportunities for poor people, where the exploitation of ICT opportunities depends on infrastructure, accessibility and human capacity. ICT, therefore, has a positive effect on human development in the case of middle and low-income countries (Osterwalder, 2003; Karaman, Ježić and Zaninović, 2021). At the national level, the Thai government is driven by the concept of NII to formulate a "Digital Thailand" policy, which aims to encourage industries to adopt new technologies through public policy and infrastructure construction projects. For example, broadband infrastructure by creating a network of the internet and encouraging the public, private, and people to utilize the internet continuously.

From 2001-2020, Thailand's policies have led to the development and application of the ICT system to the digital economy development and the quality of life of the people. The National ICT Master Plan was formulated in 2002 to achieve results by 2006. In the second phase, the Smart Thailand 2020 policy was launched in 2014. Such policy was deemed concrete and tangible as ICT is critical in building a sustainable, information-rich society and creating equal opportunities for the people. To drive the application of digital technology to benefit the economy, society, culture, and security and reduce social inequality, the Digital Economy Promotion Agency (DEPA) has sought to develop the digital capabilities of students and industrial workers. Infrastructure has also been developed to increase the competitiveness of entrepreneurs, create digital innovation, and improve the quality of life of people at all levels, including informal workers, the elderly, and the disadvantaged.

Entering the new information and economic world, Thailand faces opportunities to support the exponential growth from technological advances. However, threats exist from unequal access to information and knowledge, possibly leading to economic and social disparities in income, education, workforce, and health. If the disparity is not resolved, it will lead to the deterioration of human resource development in the future and undermine the country's development potential in the long run. Therefore, one of the fundamental challenges for all aspects of Thailand's public policy is a reduction of inequality between individuals and groups. The question is, can a country's technology reduce inequality? This research aims to examine the impact of technology policy on various aspects of inequality, including education, workforce, and healthcare and to conduct in-depth heterogeneity and decomposition analysis. An overview of studies covering the impact of policies on multiple aspects of inequality can provide a clearer view of the effects across the country. The results of this study will add new insights for development and will then be helpful for policymakers to determine the appropriate direction.

This study is analysed using a Socioeconomic survey from the NSO covering 1988 to 2019 to compare households by ICT penetration before and after policy implementation. The preliminary data showed a difference in the intensity of ICT penetration in the early stages of ICT policy implementation. However, the gap has narrowed after subsequent policies. At the household-level data, the baseline specification applying DiD and Quantile DiD approaches indicates a positive impact from ICT policies on earnings and shows ascending disparities between each quantile. However, the policy increases years of schooling while reducing educational expenditure with significant differences between regions. In addition, healthcare has been positively impacted by ICT policies. That probably means more healthcare investment for the household. The heterogeneity analysis in household attributes is a method to obtain a more precise reflection of inequality. Municipal households have a more significant advantage from policies over non-municipality. Likewise, ICT multimodal user households benefit more from policies than others. Agricultural households, however, have fewer gains from policies than industrial and service households.

By calculating the inequality with the Gini coefficient to analyze the data at the provincial level, it was found that the results showed more clearly the impact of ICT policies on inequality. ICT policies appear to have an impact on reducing income and educational (measured by years of schooling) disparities while contributing to increased expenditure in education and healthcare. In order to provide a deeper analysis to reflect the disparity, the Gini decomposition analysis was considered to compare the impact on subgroups. When sub-grouped by area, the results indicate that municipal areas are more affected by ICT policies than non-municipal areas. Decomposed by the economic sector, the ICT policies have reduced inequality in the agricultural sector in all aspects; however, for the industrial sector, inequality continues to increase. In the service sector, income and educational (measured by years of schooling) inequality have decreased. In contrast, the inequality in expenditure in education and healthcare is higher due to ICT policies.

In general, these results seem to support the objectives of the government's ICT policies in reducing inequality in income and education. However, expenditure disparities in education and healthcare persist. Policymakers should be concerned about these issues and urgently address them because they reflect differences in human capital. In addition, guidelines should be thoroughly considered to reduce the gap between households in different areas, ICT usage skills and occupations in each economic sector so that households can benefit from policies equally.

The rest of the paper is organised as follows. Section 2 discusses the related literature in more detail and frames the contributions. Section 3 studies the policy environment and describes the data and empirical strategy. Section 4 presents difference-in-differences estimates of the impacts of technology policy on outcomes that reflect labour force, education and healthcare by analysing data at the household and province levels. It also shows the heterogeneity and decomposition analysis. The last section concludes.

2 Related Literature

There are different ways that technology can impact inequality when considering the disparity in access to technology or the digital divide is a difference between those who can and cannot access technology, particularly the internet. The inability to utilize online search for information prevents access to some new knowledge and experience (Liu, 2010), including government services. This situation may increase the economic gap between urban and rural people. The inaccessibility of digital technology reflects inequality among the population and produces harmful effects on a country's economic and social dimensions (Thomas, 2017). The internet cost is extravagant for low-income families, even though it should be a basic infrastructure of services accessible to everyone. Inequality in accessibility among households is evident, particularly when comparing urban to rural areas.

Rapid technological change, innovation, and globalization are often viewed as fundamental and interconnected, increasing income inequality. Allen (2017) described the relationship between technology and inequality as to why inequality is increasing in the digital world, which can be explained in two significant schools of thought: the 'technological' school and the 'institutional context' school. The first school emphasizes that technology leads to the change in demand for work skills, and this group will have higher earnings creating a disparity between labour skill groups. The second school focuses on the economic rules of the game, such as taxation, regulation, and corporate governance, that inequality increases because the rules of the economic game are written to support wealthy and influential people.

In empirical research, Krueger (1993) surveyed demographics to determine whether workers who use computers at work receive higher wages than those who do not. The study results showed that employees who use computers receive higher wages. In addition, the results of the estimate suggested that workers who use computers directly at work earn 10 to 15 percent higher wages. These results support technological change, and in particular, the distribution of computers in the workplace contributes significantly to the change in wage structures. This is evident according to the SBTC hypothesis. Furthermore, many economists argue that computers have made skilled workers more productive, so the rapid advancement of inequality coincided with the advent of the era of computers (Autor, Levy and Murnane, 2003).

Faggio, Salvanes and Van Reenen (2010) examined evidence to explain the widespread wage inequality in the United States, the United Kingdom, and many other countries since the start of the 1980s. They found that the diffusion of new technologies across different companies increased productivity and wage spread and highlighted those industries with the most rapid increase in ICT usage, with the fastest growing productivity. In addition, the industry with the faster growth of ICT has shifted the demand for middle-educated workers to highly-educated workers. These findings are aligned with ICT-based polarization (Michaels, Natraj and Van Reenen, 2014). ICT is increasingly replacing regular jobs, causing tremendous changes in the labour market. As machines perform more routine tasks, there is a negative impact of ICT on middle-skilled workers. This is following task-biased technical change (Van Reenen, 2011). Acemoglu and Pascual's study (2020) also clearly demonstrated the technological effect of robots on employment and wages. In addition to the increase in wage inequality due to computer technology which divides labour skills into high and low-skilled workers, there is an in-depth analysis of wage structure in various dimensions such as gender, race, years of education, and educational degrees (Card and DiNardo, 2002). However, some studies from developing countries indicate that ICT can reduce income inequality depending on financial development, level of ICT adoption or accessing the type of ICT (Tchamyou, Erreygers and Cassimon, 2019; Patria and Erumban, 2020; Jing, Ab-Rahim and Baharuddin, 2020).

Aside from income and wealth issues, which are forms of economic inequality, other forms of inequality include gender, ethnicity, education, and health (Allen, 2017). One of the roots of inequality is the inequality in education that prevents low-income children from furthering their studies. This limits the young generation's access to knowledge and ability to revive and improve their livelihood to be better than their parents, thus creating a repetitive cycle of poverty. Hence, inequality in education is a more severe problem as it not only hurts the chances of poor children to get ahead but also affects the supply of high-skill labour.

The change in communication technology plays a vital role in social life and creates new opportunities in education. The developments in communication technology are helping reduce distances and connect the world through the internet. However, the ability to use the same technology of all humanity at the same level is controversial. Some people are not educated enough to use this technology; furthermore, they do not have the exact source of finance (Büyükbaykal, 2015). Investing in ICT can significantly contribute to raising the education standard, and ICT can help improve students' success. When estimating the causal effects of ICT investments on educational standards to identify the causal impact of ICT expenditure on student outcomes, evidence shows a positive impact of ICT investment on educational efficiency in UK elementary schools (Machin, McNally and Silva, 2007).

However, the impact of technology on educational gaps may be somewhat optimistic. Policy selection and technological innovation can exacerbate family inequalities (Jacob *et al.*, 2016). Students from low-resourced families with less access to support or have lower previous skills may need to be in a position to reap these benefits, and inequality may increase. The fact that inequality arises among young people due to the use of information and communication technology makes this situation a severe risk of marginalisation for people without ICT access. For example, young people with jobs and higher education are more able to use the internet for higher levels of training and work (Sánchez-Antolín; Ramos and Blanco-García, 2014). Therefore, it can be said that rapid advances in technology have exacerbated discrepancies in education and skills. Lack of access to technology threatens to increase education inequality.

Besides income disparity, workforce, and education, there is another aspect that is equally important to humans, namely healthcare. Since advances in telecommunication and computer lead to significant changes in other aspects, there are also expectations for opportunities to increase the cost-effectiveness and quality of healthcare services. Information technology has opened up guidelines for ensuring optimal healthcare quality obtained at a reasonable cost. In particular, the rapid growth of the internet community is seen as a factor that will radically change healthcare delivery models (Duplaga, 2004) both in terms of quality and access to healthcare services.

As the world increasingly digitizes, another social stratification must be added to the inequality list between rural and urban people. That is access to digital technology, which is required by all sectors. However, healthcare will have tremendous demand (Walker, 2019). Therefore, there is an urgent need for digital health policies that consider affordability, credibility, and capacity building in communities to develop digital technology skills and methods for implementing digital health interventions. In general, health inequality has been described in terms of disproportionate disease burden or behavioural risk factors encountered by a subset of the population. In the United States, most research has focused on racial/ethnic health inequality. While in other developed countries, most research has focused on health-based inequality, socioeconomic status (SES), or class (Bleich *et al.*, 2012). The study of Wagstaff (2002), which linked health inequality to income, showed that increased income appears to be associated with increased health inequality. Evidence from trends in health inequality in both the developing world and the industrialized world supports the idea that health inequality is increasing with increasing per capita income. The link between health inequality and per capita income is likely the result of technological change, coupled with economic growth and a tendency for the better-offs to absorb new technology ahead of the poor.

ICT has become a necessity for healthcare. However, what happens to people being left behind or abandoned by this technological revolution, as the internet is increasingly used to communicate health knowledge, and there is a growing belief that it can help transform personal and public health? Lindsay *et al.* (2008) used a randomized controlled trial to test access to an internet health portal to improve the outcomes of people with heart disease. The findings have implications for the health divide and widened inequalities. This intervention provides not only a significant difference in health-related behaviours and health quality of life in heart disease patients but also the balance of benefits and costs in economic terms to broader health and social services. Among other health-related issues, such as alcohol consumption and smoking, a study by Gupta *et al.* (2016) looked at adolescent groups on the effects of internet media on motivating adolescents to drink alcohol. However, internet use is positively and negatively correlated with alcohol consumption, depending on internet use behaviour (Svensson and Johnson, 2020). At the same time, some studies have shown that internet-accessible smokers are more likely to change their smoking habits. If given the appropriate information, it can assist in smoking cessation (Civljak *et al.*, 2013; McCrabb *et al.*, 2019), but if internet users were at high risk of internet addiction, it would possibly lead to more smoking prevalence (Sung *et al.*, 2013; Salici, 2020).

In summary, technology creates many benefits in many fields. Nevertheless, it also has a negative impact, especially generating a multi-dimensional inequality across different areas and populations. Therefore, understanding the impact of technology policy on inequality is a significant challenge and needs to be addressed to influence appropriate policy-making and implementation.

3 Background and Empirical Strategy

Since Thailand's adoption of internet technology in 1987, the internet was initially used only in the academic circles of universities and government agencies. Then, the application of internet users for the development of universities and secondary education, mainly located in urban areas, was promoted during 1995-1996. In 2001, the government realized the importance of this technology and wanted to use it to spread prosperity into remote rural areas and reduce inequality. This led to the initiation of the Sub-district Internet policy. That started technology infrastructure expansion into sub-districts across the country through local government controls. In 2003-2004, a policy to provide affordable internet-compatible computers was initiated, along with the continuation of technology infrastructure development leading to the founding of the Community Internet Center in 2007, distributed in various important places. Five years later (2012), the ICT Free Wi-Fi policy was established to support the One Tablet Per Child policy that distributed tablets to elementary school students across the country. Unfortunately, at that time, many schools in remote areas had problems accessing the internet due to installation agencies' failure to operate due to unworthy investment. In 2016, the government launched the Village Broadband Internet or Net Pracharat policy to expand the installation of internet signals to cover remote areas with subsidies from the government. With the evolution of the mentioned policies, Figure 1 clearly reflects the result of ICT policies due to the continuously increasing trend of internet users.

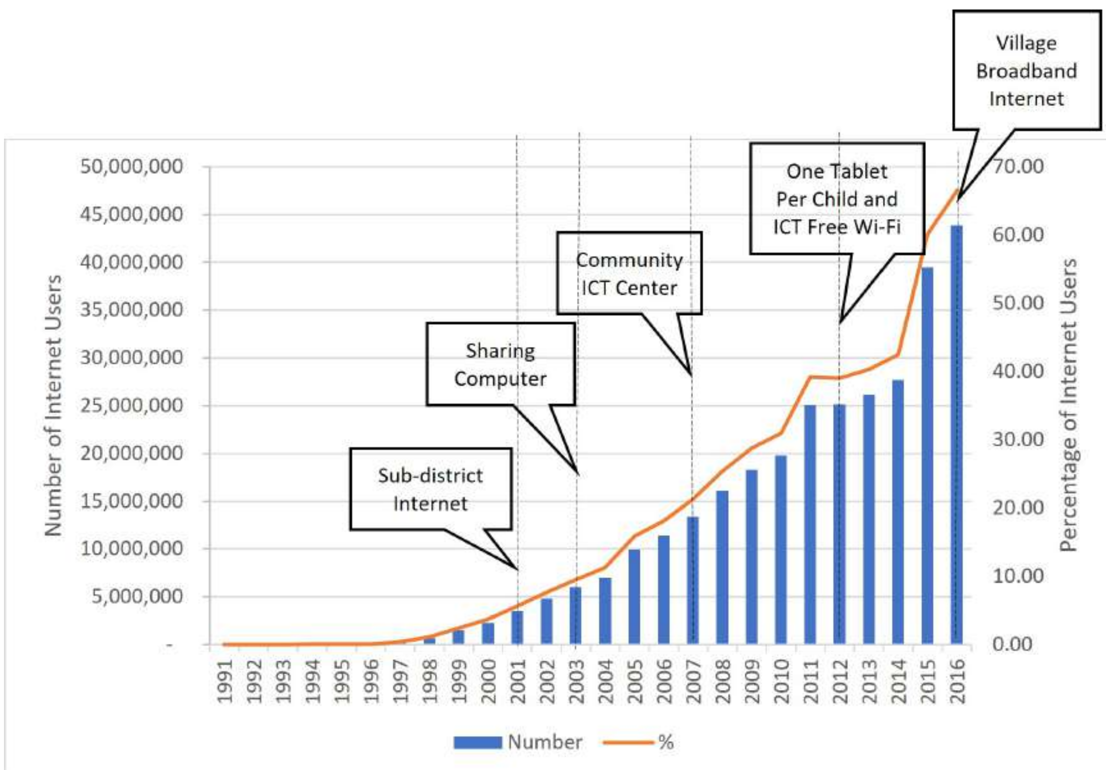


Figure 1: The growth of internet users during the evolution of ICT policies
Source: NECTEC (2020).

While technology usage improves productivity, accelerates economic growth, enables knowledge and information sharing, and increases access to essential services, the distribution of benefits is disproportionate, thus likely causing inequality. The country must implement technology used effectively as the future modern world is more complex, full of uncertainty and changes with high impact. An example is the Covid-19 crisis, which has had severe impacts on a global scale and reflected inequality even more clearly in various aspects. This Covid-19 outbreak has forced many students to study from home, but many lack the technology necessary for remote learning, making them vulnerable to educational disadvantages. The public's access to government remedies required registration or enrollment, and smartphone implementation underscores the disadvantages of the poor and marginalized. This increases inequality further.

I. Data

This study relies on a data source from Thailand's National Statistical Office (NSO). The data sets are Socioeconomic Survey (SES) that cover five regions, 77 provinces whose areas are separated into 5,300 non-municipalities and 2,474 municipalities. Data include NSO public opinion polls primarily, going back to 1988, which has over 50,000 observations annually (each providing status at both the household and individual level). However, the family size has been selected from households with more than two generations since this study aims to consider three aspects: labour force, education and healthcare. Therefore, each generation in a household could provide more comprehensive answers. In total, 78,254 households from 17 years are used in the study. Variable definitions and their descriptive statistics on all variables used are displayed in Appendix Table A.1.

The potential outcomes employed in this empirical strategy, in an educational context, consider education attainment as an indicator used to reflect the structure and performance of the education system and to show the educational level of the population, which means the accumulation of human capital within a country. Many studies have used years of schooling as the outcome variable, for example, Duflo (2001) and Havnes and Mogstad (2015). Another influential variable is educational expenditures, which have implied educational investment and can be found in Francesconi, Slonimczyk and Yurko (2019). Regarding the labour force, work payment is a variable that indicates the work capacity of each worker. Most of the studies, therefore, use earnings or wages in the analysis, such as Ashenfelter and Card (1985), Duflo (2001), and Havnes and Mogstad (2015). Wagstaff (2002) considered medical care spending as an essential variable regarding healthcare outcomes. In comparison, Lindsay *et al.* (2008) used a randomized controlled trial to examine different variables, including alcohol consumption and smoking.

Appendix Table A.2 shows the whole and used samples from the household selection. The balance tests are used to compare samples before and after the intervention. So, there must be no statistically significant difference in the mean values. However, if the tests find significant differences in observables, these variables should be applied as control variables.

Due to the investment in the information technology infrastructure of Thailand and its ICT policies, the Key ICT indicators in the past 20 years are considered, the statistics from 1998 to 2019 of NSO survey, which this study used to analyse as shown in Figure 2. Comparing ICT device usage among households since the ICT policy launched shows that mobile phone use is exponentially increasing, and almost all households use it. Although some households have had computer use since pre-policy, household usage has increased slightly over time. Then there has been a downward trend after 2013. The vast majority of internet usage is via mobile phones, evident after the policy has been implemented, especially when the ICT Free Wi-Fi policy was valid for one year. However, the proportion of multimodal user households is still tiny, about 20%.

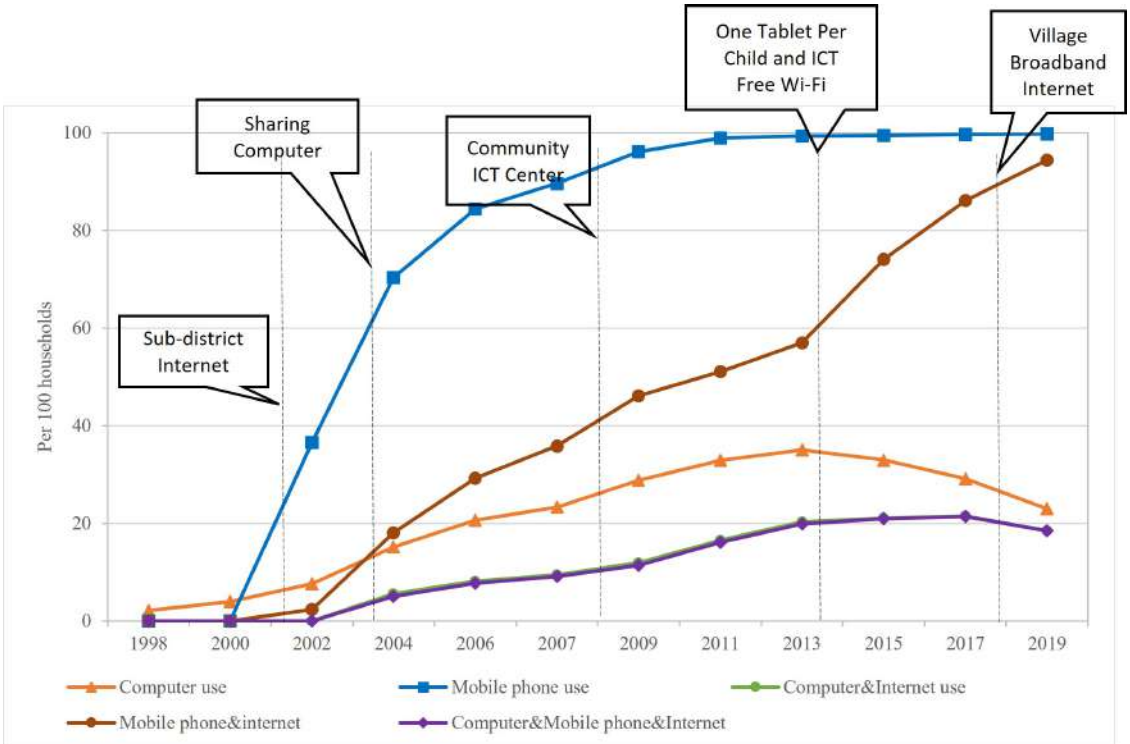
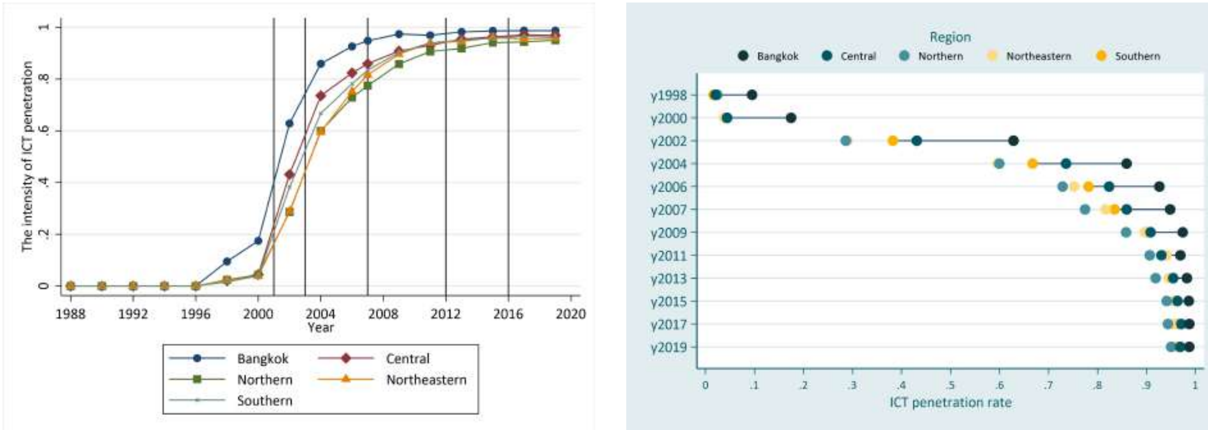


Figure 2: Percentage of households with ICT devices, 1988-2019

The vital variable used in the analysis to be the treatment variable is the intensity of ICT penetration, calculated from the number of households accessing ICT in each region for each year. Figure 3(i) reports the ICT penetration rate by region. Overall, all regions tend to grow in the same direction. However, at the beginning of the ICT policy initiation, inequalities were seen between regions, especially Bangkok, the capital of Thailand, and other regions. In 2019 there was almost complete diffusion across the country. Figure 3(ii) indicates a relatively high ICT concentration in Bangkok until 2012 the concentration began to decline. It could be that households have equal access to ICT.

The binscatter can illustrate the relationship between outcome variables and ICT accessibility of households, as shown in Figure 4. Prior to the initiation of the ICT policy, households with access to ICT were high-income, high-educated, and high-healthcare households. For alcohol consumption and smoking, there seemed to be little difference between the ICT access and the non-accessible groups. After implementing the ICT policy, providing households with more access to the internet, the average of each outcome was reduced. However, the policy had been implemented for a while, households with access to ICT appeared to have higher average outcomes in income, education and healthcare, and there was an increasing gap between those who did not have access. Household consumption of alcohol and smoking declined considerably, and there was a slight gap between the two groups with



(i) (ii)

Figure 3: The ICT penetration rate by region, 1988 – 2019
Notes: The vertical grey lines in the left figure indicate each ICT policy implementation.

and without access to ICT. When considering these graphs, households with access to ICT and those without access to ICT before and after policy implementation could be different based on counterfactual trends.

In the inequality analysis, differences in outcomes are considered by quintiles. Figure 5 shows that in the initial phase of ICT policy implementation, households at different quintiles would be in regions with relatively significant differences in the intensity of ICT penetration, evident in earnings quintiles. Households at high quintile levels are located in regions with high intensity of ICT penetration. As policy implementations take many forms and can be distributed to cover more people and areas, the difference between quintiles reduces, and each household is in a region where the intensity of ICT penetration is quite close.

The proportion of household members with internet access classified by household characteristics is shown in Figure 6. In the early stages of the ICT policy, there was an increasing gap between household members' access to the internet in municipal and non-municipal areas. However, the gap narrowed when the policy was rolled out thoroughly, even if households in municipalities had a larger share of internet access. As for the occupational patterns of households, it was found that agricultural households had a lower proportion of internet access than other households.

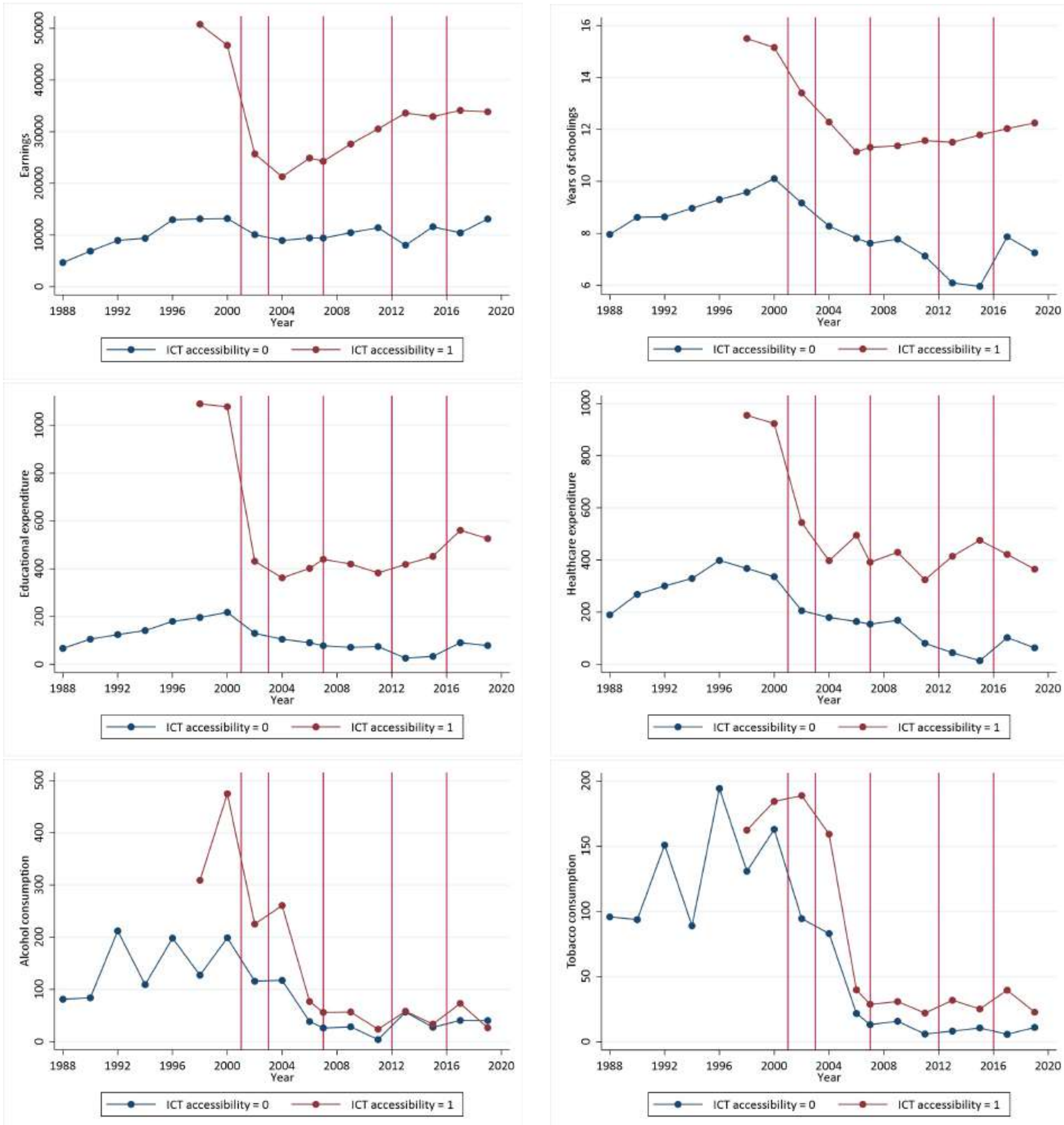


Figure 4: Household comparison with ICT accessibility in each outcome, 1988-2019

Notes: The vertical red lines indicate each ICT policy implementation.

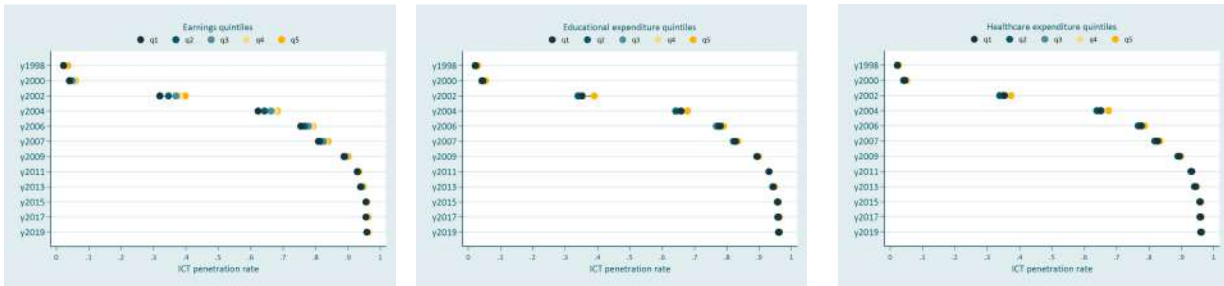


Figure 5: The intensity of ICT penetration by outcomes quintiles: earnings, educational expenditure and healthcare expenditure, 1998 - 2019

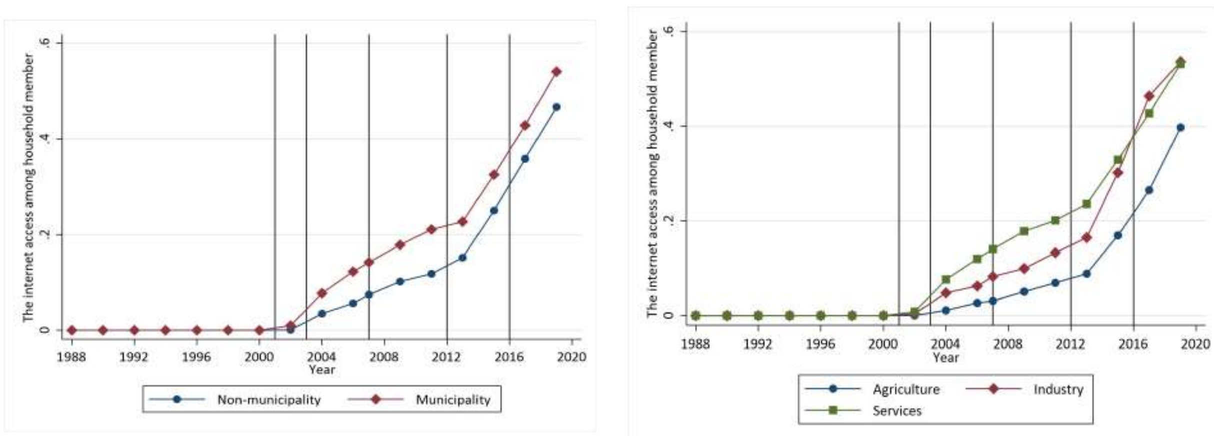


Figure 6: The share of internet access among household member by area and occupation in each economic sector, 1988-2019
Notes: The vertical grey lines in the left figure indicate each ICT policy implementation.

II. Research Methods

This study employs the difference-in-differences model to assess the effect of technology policy on inequality in Thailand in various aspects, including education, labour force, and healthcare. The DiD method has been the most widely applied quasi-experimental research design since the work by Ashenfelter and Card (1985). It is widely used to evaluate the impact of policy interventions. It has become well-known in economics and other social sciences. It can provide a more effective estimate of the impact of treatment if longitudinal or repetitive cross-sectional data is available by using additional time dimensions to estimate treatment effects under less restrictive assumptions (Athey and Imbens, 2006; Blundell and Costa Dias, 2009).

The ICT technology policy has been in operation since 2001. Therefore, the initial model setting determines the period before and after the intervention, i.e. pre-intervention: 1988-2000 and post-intervention: 2001-2019 (post-intervention will also take into account each period of the change in each policy).

One main objective of technology policy has been to encourage ICT usage among citizens, especially those in remote regions, to reduce inequality. Hence, the households in the treatment group live in a region with higher ICT access. In contrast, the baseline control group is identified from the comparable households living in a region with lower ICT access. Since the ICT policy has been implemented, it is likely to have a more substantial effect in areas with higher ICT adoption (treatment groups).

To exploit the variation in treatment across groups of units at different times, a difference-in-differences estimate of intervention impact compares pre and post-differences in treatment and comparison communities. To assess the effect of the technology policy on the potential outcomes can be generalized to the framework in order to estimate the following DD model for all outcome variables considered the main baseline specification:

$$y_{irt} = \alpha + \beta_r + \gamma_t + \delta Treat_{rt} + \omega X'_{irt} + \varepsilon_{irt} \tag{1}$$

where y_{irt} is the outcome of household i living in the region r at time t, β_r is a region fixed effect, γ_t is a year fixed effect, $Treat_{rt}$ is the treatment indicator (the ratio of ICT penetration by region), X'_{irt} a vector of control variables, and ε_{irt} is a residual disturbance. The coefficient of interest is δ, which captures treatment effect heterogeneity over time. This model notices that the treatment variable is continuous (Acemoglu, Autor and Lyle, 2004).

This research also studies the treatment effect at a given quantile based on the quantile regression approach (Koenker and Basset, 1978). It is not limited to the conditional mean but estimates values from the whole condition distribution of a dependent variable (Davino, Furno and Victocco, 2014). This model computes the counterfactual distribution by adding the change over time at the τ^{th} quantile of the control group to the τ^{th} quantile of the first-period treatment (Athey and Imbens, 2006). The approach of this application intends to compare the same quantile in different groups, which probably reflects inequality between groups more clearly. Therefore, the quantile difference-in-differences (QDiD) is an alternative approach.

$$y_{irt}^{(\tau)} = \alpha^{(\tau)} + \beta_r^{(\tau)} + \gamma_t^{(\tau)} + \delta^{(\tau)} Treat_{rt} + \omega^{(\tau)} X'_{irt} + \varepsilon_{irt} \tag{2}$$

In addition to the household level, as mentioned earlier, this study further analyses the aggregate data to provide a clearer view of inequality using the Gini coefficient (Corrado Gini, 1912). Inequality has many dimensions. Most people consider the economic or measurable dimension that relates to the income and consumption expenditure of an individual or a household. However, inequality can also be viewed from another perspective (Heshmati, 2004). This can be linked to inequality in various aspects, such as education, health, welfare, and opportunity. Therefore, this study calculates the Gini coefficient for inequality by using the earnings, years of schooling, educational expenditures and healthcare expenditures of households.

For practical implementations, the perception of overall inequality may need to be revised to target public policies reasonably. Decomposing this measure can help to understand the determinants of inequality and assist policymakers in imposing efficient policies for disparities reduction in the distribution of incomes (Araar, 2006). Decomposing inequality indices implies exploring the structure of inequality, i.e. the disaggregation of total inequality in relevant factors. The techniques used more often decompose inequality either by income source or by subpopulations. In addition, inequality can decompose at different levels of aggregation (Heshmati, 2004).

A Gini coefficient can decompose in two different approaches. First, if per capita income can be divided into several sources for the entire population, the Gini coefficient can be decomposed by income source (Shorrocks, 1982; Lerman and Yitzhaki, 1985). Second, if the total population is divided into various subgroups (for example, by gender, education level, occupation, and region), the Gini coefficient can be decomposed into three components if the population is divided into a finite number of groups (Shorrocks, 1984; Dagum, 1997): (a) within-group component arising from income variations within each group; (b) between-group component arising from the differentials of mean incomes between the groups; and (c) overlapped component. Actual policies have a very differentiated effect on subgroups of households. Hence, it is essential to distinguish overall inequality among different groups of households. In this study, applying the decomposition of Gini coefficients by subgroups is appropriate. Thus, the Gini decomposition approach that will be explored is the exclusively interesting sub-groups of households and also reflect province characteristics, including area and economic sector.

The next step to exploit the Gini coefficient as another potential outcome for assessing the effect of the technology policy, the difference-in-differences model can be generalized to the following specification:

$$y_{pt} = \alpha + \beta_p + \gamma_t + \delta Treat_{pt} + \varepsilon_{pt} \tag{3}$$

where y_{pt} is the Gini index (overall and decomposition) of province p at time t, β_p is a province fixed effect, γ_t is a year fixed effect, $Treat_{pt}$ is the treatment indicator (the ratio of ICT penetration by province), X'_{irt} a vector of control variables, and ε_{pt} is a residual disturbance.

4 Empirical Findings

I. Household Level

The results in Tables 1-3 are based on equations (1) and (2) described above, illustrating the effect of ICT policy on different outcomes with region and year fixed effects. This study initially estimates coefficients by employing DiD approach, and Quantile DiD techniques, which allow coefficients to vary at different quantiles, τ: the 10, 25, 50, 75 and 90 percent quantiles.

How key variables of this study (ICT policy) significantly affect household earnings and different earnings levels are selectively discussed. Regarding the results in panel A in Table 1 and Appendix Table A.3, the estimated coefficients associated with *reg_ict* (ICT penetration) and *lnavg_inc* are significantly positive and increase across quantiles except for lowest-income households (τ=0.10). This means economically stronger households benefit more from Information technology investment, which probably increases inequality.

Table 1: Effect of ICT policies on earnings

	DiD	**Quantile DiD**				
		τ=0.10	τ=0.25	τ=0.50	τ=0.75	τ=0.90
Panel A Labour force						
−**Monthly income:** *lnavg_inc*						
reg_ict	0.150**	0.165	0.168**	0.186**	0.153**	0.191*
	(0.061)	(0.122)	(0.066)	(0.050)	(0.075)	(0.106)
$R^2/PseudoR^2$	0.762	0.518	0.553	0.559	0.533	0.489
Observations	78,254			78,254		
Controls	Yes			Yes		
Region FE	Yes			Yes		
Year FE	Yes			Yes		

Notes: Each pair of rows reports the coefficient estimate and the associated standard error in parenthesis. $***$, $**$ and $*$ denote statistical significance at the 1%, 5% and 10% significance levels, respectively.

When considering other panels, panel B in Table 2 (see more results in AppendiX Table A.4) reports the impact of ICT penetration on years of schooling and educational expenditure. These models reveal that the estimated coefficients associated with ICT penetration and *highedu* (years of schooling) are significantly positive. However, they do not rise across quantiles and are not statistically significant in the lowest-educated households. While another educational outcome (*lnedu_exp*) is affected in the opposite sign, i.e. the educational expenditure is significantly negative and declining in higher quantile. Households with higher education investments would be encouraged by ICT policies to cut this cost significantly.

Table 2: Effect of ICT policies on education

	DiD	Quantile DiD				
		τ=0.10	τ=0.25	τ=0.50	τ=0.75	τ=0.90
Panel B Education						
−**Years of schooling:** *highedu*						
reg_ict	0.799***	-0.745	-0.017	0.892*	1.901***	1.222*
	(0.463)	(0.600)	(0.478)	(0.539)	(0.678)	(0.710)
$R^2/PseudoR^2$	0.398	0.156	0.213	0.278	0.271	0.150
Observations	78,254			78,254		
−**Education expenditure:** *lnedu_exp*						
reg_ict	-0.996***	-0.262	-0.915***	-1.021***	-0.986***	-0.671**
	(0.175)	(0.287)	(0.319)	(0.265)	(0.275)	(0.275)
$R^2/PseudoR^2$	0.334	0.137	0.155	0.198	0.250	0.272
Observations	58,503			58,503		
Controls	Yes			Yes		
Region FE	Yes			Yes		
Year FE	Yes			Yes		

Notes: Each pair of rows reports the coefficient estimate and the associated standard error in parenthesis. $***$, $**$ and $*$ denote statistical significance at the 1%, 5% and 10% significance levels, respectively.

Table 3 and Appendix Table A.5 consist of three sets of specifications that show findings based on the dependent variables: healthcare expenditure, alcohol consumption, and tobacco consumption. The impact of ICT penetration on healthcare expenditure (*lnhealth_exp*) is significantly positive. However, when analyzing the QDiD model, the coefficients were insignificant, and they appear to not increase across quantiles. At the same time, ICT penetration did not affect alcohol consumption (*lnalcohol*) because the estimated coefficients were not statistically significant. For another healthcare outcome, the effect of ICT penetration on smoking (*lnsmoking*) is significantly positive and increases across quantiles.

Table 3: Effect of ICT policies on Healthcare

	DiD	Quantile DiD				
		τ=0.10	τ=0.25	τ=0.50	τ=0.75	τ=0.90
Panel C Healthcare						
−**Healthcare expenditure:** *lnhealth_exp*						
reg_ict	0.399*	0.291	0.029	0.349	0.631***	0.381
	(0.227)	(0.436)	(0.365)	(0.356)	(0.177)	(0.319)
$R^2/PseudoR^2$	0.135	0.054	0.069	0.078	0.087	0.095
Observations	56,301			56,301		
−**Alcohol consumption:** *lnalcohol*						
reg_ict	0.005	0.373	-0.065	-0.126	0.446	-0.598
	(0.221)	(0.482)	(0.339)	(0.297)	(0.300)	(0.372)
$R^2/PseudoR^2$	0.376	0.189	0.202	0.217	0.226	0.232
Observations	19,376			19,376		
−**Tobacco consumption:** *lnsmoking*						
reg_ict	0.804***	0.439**	0.645*	1.078***	1.289***	1.010***
	(0.210)	(0.223)	(0.339)	(0.263)	(0.333)	(0.339)
$R^2/PseudoR^2$	0.394	0.231	0.242	0.236	0.229	0.211
Observations	33,404			33,404		
Controls	Yes			Yes		
Region FE	Yes			Yes		
Year FE	Yes			Yes		

Notes: Each pair of rows reports the coefficient estimate and the associated standard error in parenthesis. $***$, $**$ and $*$ denote statistical significance at the 1%, 5% and 10% significance levels, respectively.

Heterogeneity analysis

This study's main objective was to analyse ICT policies' effects on inequality. The issue of the further study was the inequality between households with different characteristics. Therefore, the attributes of households that ICT policies will likely make a difference are considered in this section. The previous empirical results based on the overall sample may not incorporate household differences with locations, ICT usage patterns and occupation in economic sectors.

Regarding household location, they considered that households in municipal areas are likely to benefit from the ICT policies more than in non-municipal areas. This is consistent with the study findings that the estimated coefficients are significantly positive for all outcomes compared with the base (non-municipal area). Many forms of ICT devices in the household, including computers or mobile phones, are connected to the internet and not connected. However, only 20% of all households use all three devices, as shown in Figure 3. According to the study of these usage differences, multimodal users benefit from the ICT policies more in outcomes than other users. This can notice from statistically significant positive coefficients. As for occupational patterns of households, this study classified occupational patterns by economic sector as agriculture, industry and services, with non-agricultural sectors being based. The results showed significant negative coefficients across all outcomes. These indicate that households in the agricultural sector are disadvantaged in implementing ICT policies compared to other households. This may be due to remote location or unskilled work.

Table 4: Effect of ICT policies on outcomes in different household attributes

	Panel A Labour force	**Panel B Education**		**Panel C Healthcare**		
	Earnings	**Years of schooling**	**Education expenditure**	**Healthcare expenditure**	**Alcohol consumption**	**Smoking**
reg_ict × municipal area	0.028***	0.797***	0.207***	0.082***	0.109***	0.354***
	(0.004)	(0.031)	(0.015)	(0.020)	(0.018)	(0.020)
reg_ict × multimodal user	0.085***	1.529***	0.719***	0.303***	-0.008	0.301***
	(0.007)	(0.040)	(0.023)	(0.031)	(0.029)	(0.038)
reg_ict × agricultural sector	-0.114***	-1.295***	-0.355***	-0.056***	-0.081***	-0.297***
	(0.006)	(0.039)	(0.018)	(0.024)	(0.022)	(0.022)
Observations	78,254	78,254	58,503	56,301	19,376	33,404
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each pair of rows reports the coefficient estimate and the associated standard error in parenthesis. $***$, $**$ and $*$ denote statistical significance at the 1%, 5% and 10% significance levels, respectively.

II. Province Level

Considering the aggregate level data in the study of the impact of ICT policies on inequality by calculating provincial inequality with the Gini coefficient, the analysis is divided into three aspects as in the previous study on household-level data, i.e., labour force (measured by earnings), education (measured by years of schooling and educational expenditure) and healthcare (measured by healthcare expenditure). The relationship of ICT penetration to inequality in each aspect differs in various forms. These are illustrated by Figure 7, which plots trends in each outcome inequality as defined by ICT penetration rate from 1988 to 2019. Before implementing the ICT policy in 2001, inequality tended to increase in income and healthcare. After implementing the policy, income inequality decreased continually. The healthcare viewpoint was still seen as a disparity rise; however, the slope of the graph was more flattened. The education aspect, measured by expenditure, was given the exact correlation to the healthcare side. Meanwhile, measured by years of schooling, the disparity was reduced before the implementation of ICT policy and decreased significantly after the implementation. That noticed graph has a more negative slope.

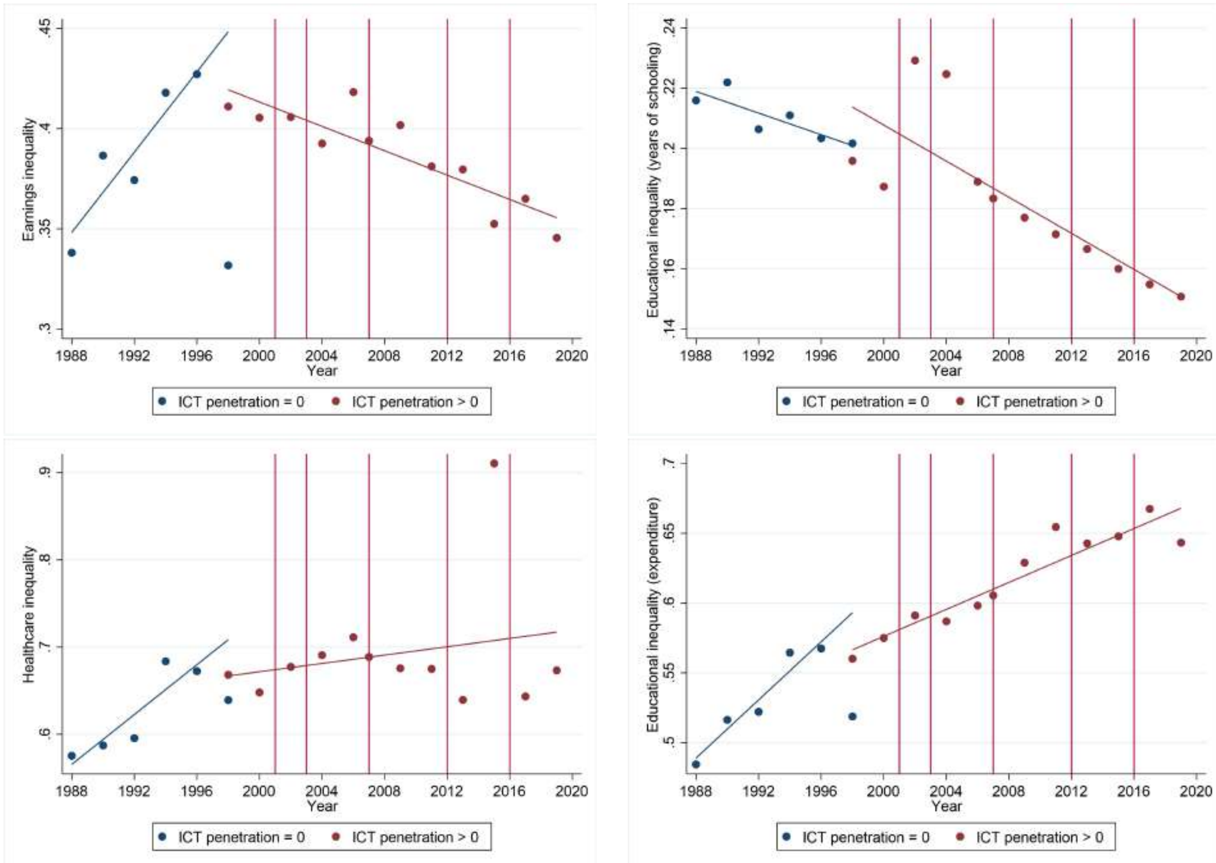


Figure 7: The intensity of ICT penetration in each Gini outcome, 1988-2019
Notes: The vertical red lines in the left figure indicate each ICT policy implementation.

Table 5 displays the results from estimating equation (3) with the Gini coefficient from earnings, years of schooling, educational expenditure and healthcare expenditure as outcomes with/without province and year fixed effects. The models that provide statistically significant coefficients report that the estimated coefficients associated with ICT penetration and earnings and ICT penetration and years of schooling are significantly negative. However, there appears to be a significant positive impact of ICT policy on expenditure inequality in both education and healthcare aspects. As these results show, the impact of ICT policies on inequality can be seen more clearly. While the household data analysis, ICT policies have been shown to increase the distribution of some outcomes at different levels; it is still being determined whether the inequality increased.

Table 5: Effect of ICT policies on inequality (Gini coefficient)

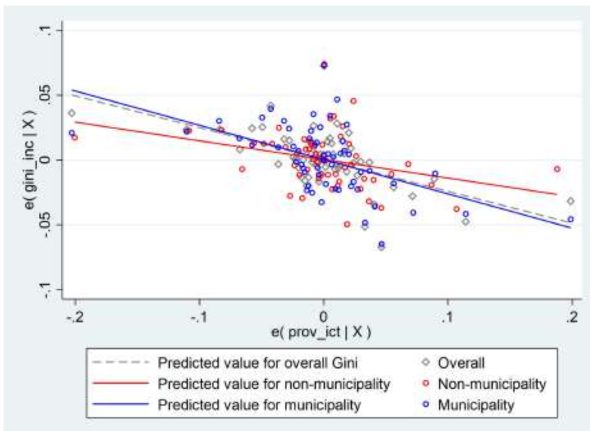
	Gini coefficient			
	(1)	(2)	(3)	(4)
Panel A Labour force: Earnings				
prov_ict	-0.023***	-0.020***	-0.241***	-0.008
	(0.006)	(0.005)	(0.040)	(0.055)
R^2	0.013	0.013	0.108	0.092
Observations	1,287	1,287	1,287	1,287
Panel B Education: Years of Schooling				
prov_ict	-0.044***	-0.042***	-0.165***	-0.099***
	(0.002)	(0.002)	(0.016)	(0.018)
R^2	0.266	0.266	0.503	0.496
Observations	1,287	1,287	1,287	1,287
Educational expenditure				
prov_ict	0.104***	0.104***	-0.045	-0.050
	(0.007)	(0.006)	(0.046)	(0.065)
R^2	0.181	0.181	0.234	0.234
Observations	1,286	1,286	1,286	1,286
Panel C Healthcare: Healthcare expenditure				
prov_ict	0.076***	0.077***	-0.019	0.118
	(0.009)	(0.008)	(0.065)	(0.078)
R^2	0.065	0.065	0.306	0.304
Observations	1,287	1,287	1,287	1,287
Province FE	No	Yes	No	Yes
Year FE	No	No	Yes	Yes

Notes: Each pair of rows reports the coefficient estimate and the associated standard error in parenthesis. $***$, $**$ and $*$ denote statistical significance at the 1%, 5% and 10% significance levels, respectively.

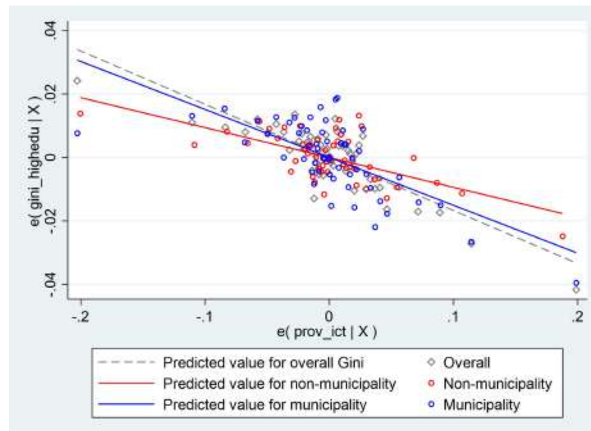
Decomposition analysis

To disentangle the ways by which inequality is affected due to ICT policies, they are decomposed into their components and compute the Gini index for each component by selecting from potentially interesting subgroups. First, sub-grouped by area are municipalities and non-municipalities. ICT penetration has a more significant disparity reduction in municipal areas than non-municipal areas in all outcomes, as shown in Appendix Table A.9. The yield coefficients of the municipality coefficients were higher than those in the non-municipal coefficient models.

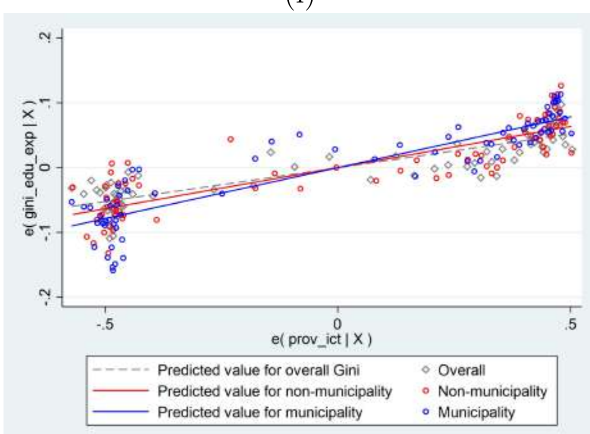
Figure 8 depicts the relationship between ICT penetration rate affected inequality measured by the Gini index after controlling for province and year fixed effects. The difference can be seen between municipal and non-municipal areas, where the municipal slope of diagrams is steeper than the non-municipal one across all inequality outcomes, whether the slope is positive or negative, reflecting the more significant impact of ICT. For overall (within-province) inequality, their graphs show a similar pattern to between-group inequality. However, the effect sizes are smaller in expenditure inequality in education and healthcare aspects. At the same time, the impact is higher than when employing the years of schooling outcome. ICT policies have a higher impact on inequality in municipalities; it is likely that because municipal areas have more access to ICT than non-municipal areas, there could reap more benefits from ICT policies. It is consistent with the previous study from household-level data.



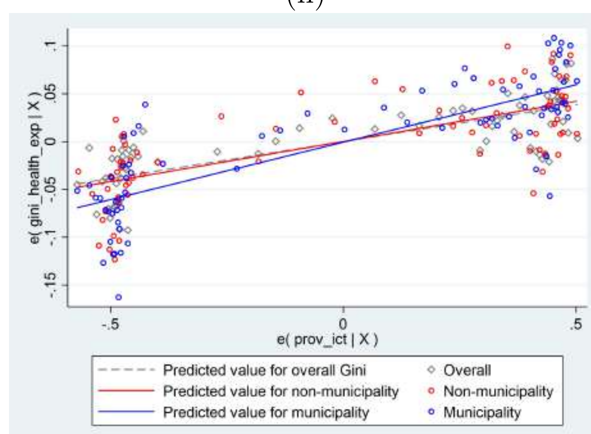
(i)



(ii)



(iii)



(iv)

Figure 8: Association between Gini coefficient and ICT penetration, by area

Second, inequality is decomposed by economic sectors, including agriculture, industry and service. As a result of income and educational inequalities, measured by years of schooling in Appendix Table A.10, ICT policies reduced inequality in the agriculture and service sectors, while the industrial sector increased inequality. Analysing the disparities in education and healthcare expenditures was found that ICT policies reduced the disparities only in the agricultural sector. The inequality in the industrial sector seems to persist despite the ongoing implementation of ICT policies. It is possible that the different impacts of ICT are related to the labour force's skills in different economic sectors.

The direction and magnitude of the impact of ICT policies on all three aspects of inequality by the economic sector sub-group can be demonstrated in Figure 9. The impact size on within-province inequality was similar to between-groups except for expenditure issues in education and healthcare, which have a more substantial impact at decomposed by agriculture and industrial sectors.

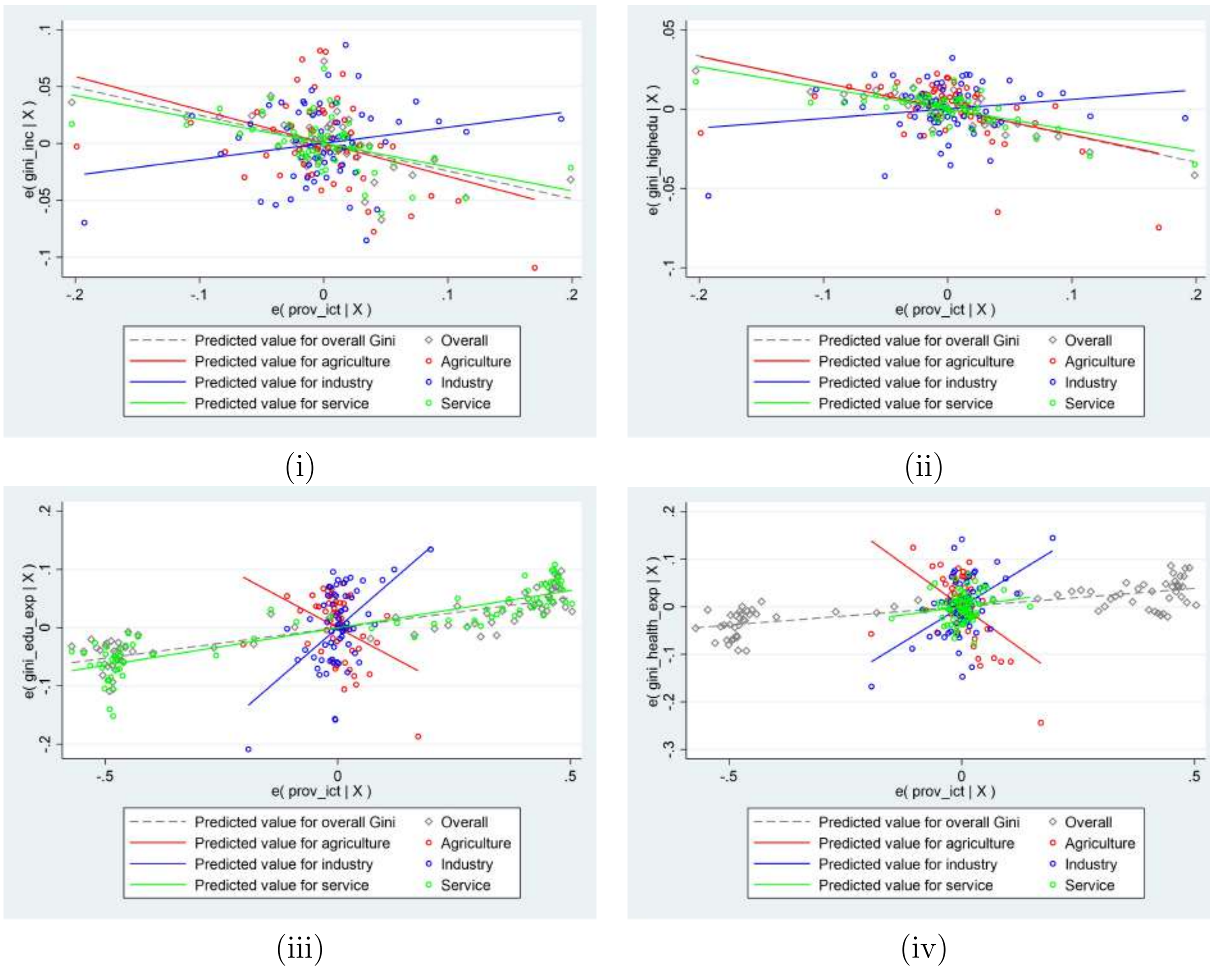


Figure 9: Association between Gini coefficient and ICT penetration, by economic sector

Robustness Check

Since the Gini coefficient has a primary weakness, it cannot differentiate different kinds of inequalities measurement. Apart from this limitation, it is susceptible to inequalities in the middle part of the income distribution (De Maio, 2007). Therefore, to test the sensitivity of the results for the Gini coefficient, the percentile ratios are considered a simple method but an effective way to examine inequality. For example, the correlation between population outcomes may be compared with the ratios 90:10, 70:30, and 60:40. This is a vital advantage of this measure to allow sensitivity analysis. The robustness check will employ the P90/P10 ratio by calculating for comparison the income earned by the top 10% of households and the income earned by the poorest 10% of households (in the case of income variable). Higher percentile ratio values indicate a wider net income percentiles gap (Costa and Pérez-Duarte, 2019).

The results of the replication analysis with alternative inequality measures are presented in Table 6. ICT policies affect inequality not only measured by the Gini coefficient but also by the percentile ratio (P90/P10), in which the estimated coefficients are the same direction and have statistically significant from the same model.

Table 6: Effect of ICT policies on inequality: Alternative inequality metrics, P90/P10

	P90/P10			
	(1)	(2)	(3)	(4)
Panel A Labour force: Earnings				
prov_ict	-1.676***	-1.605***	-7.608***	-2.194
	(0.197)	(0.178)	(1.143)	(1.995)
R^2	0.062	0.062	0.105	0.097
Observations	1,287	1,287	1,287	1,287
Panel B Education: Years of Schooling				
prov_ict	-0.598***	-0.588***	-1.047***	-0.022
	(0.046)	(0.042)	(0.277)	(0.445)
R^2	0.135	0.135	0.234	0.229
Observations	1,287	1,287	1,287	1,287
Educational expenditure				
prov_ict	28.505***	28.825***	-1.244	-8.235
	(2.877)	(2.624)	(14.685)	(28.385)
R^2	0.079	0.079	0.160	0.159
Observations	1,286	1,286	1,286	1,286
Panel C Healthcare: Healthcare expenditure				
prov_ict	546.266***	549.335***	-67.996	184.190
	(125.817)	(117.170)	(384.743)	(1176.772)
R^2	0.017	0.017	0.230	0.230
Observations	1,287	1,287	1,287	1,287
Province FE	No	Yes	No	Yes
Year FE	No	No	Yes	Yes

Notes: Each pair of rows reports the coefficient estimate and the associated standard error in parenthesis. $***$, $**$ and $*$ denote statistical significance at the 1%, 5% and 10% significance levels, respectively.

5 Conclusions and Policy Implications

Since Thailand's implementation of ICT policies from the past to the present has many variations but has the same objective: to be a tool to reduce the inequality that is a problem in most developing countries. This study aimed to evaluate the impact of ICT policies on disparities in areas including labour force, education and healthcare using a Socioeconomic survey at the household level from NSO.

In the early stages of the ICT policy implementation, there was a relatively high gap in inequality between regions where the intensity of ICT penetration was concentrated in Bangkok. However, in the later periods, the gap gradually decreased. It concluded that households in each region have equal access to ICT.

To study the impact of ICT policies on inequality, the DiD and Quantile DiD approaches are used. For household-level data, the empirical results from baseline estimates report that ICT penetration is found to have an increasing effect on earnings and with the level of quantiles. Regarding education, ICT policies have encouraged increasing educational attainment and reducing the disparity between regions. The policies, meanwhile, help reduce the cost of education, although higher quantiles have a more significant impact. For the healthcare aspect, ICT policies enhance access to healthcare, even if there are differences between regions. On the other hand, smoking is also positively affected by policy and increases in quantile levels. To further study the inequality, household attributes are compared. Households in municipal areas would benefit more from ICT policies and ICT multimodal user households. However, agricultural households benefit from the policy less than other groups. It could mean significant inequalities in policies between different household groups.

Based on aggregate data analysis at the province level, this study applies the Gini coefficient to measure inequality. The results provide more clarity in interpretations of the impact of ICT policies on inequality. Income and educational (years of schooling) disparities declined after the policy was implemented, while expenditure disparities in education and healthcare had a higher positive impact. In addition, the effect on the disparity between subgroups is compared by decomposition. The results are consistent with the analysis of household-level data when sub-grouped by area. Municipalities are more affected by ICT policies than non-municipal areas as there possibly have more ICT accessibility. Analysing the impact of policy by the economic sector, inequality is reduced in the agricultural sector in all aspects, while the industrial sector is indicated as increasing inequality. In the service sector, income and educational (measured by years of schooling) disparities have decreased, but expenditure disparities in education and healthcare have increased. The different impacts of ICT policies on inequality decomposed by the economic sector could be related to the labour force's skills in different sectors.

As the results of this paper, it appears that Thai people can benefit from ICT policies by enabling them to increase their earnings and improve income distribution, thereby reducing income inequality (Tchamyou, Erreygers and Cassimon, 2019; Patria and Erumban, 2020; Jing, Ab-Rahim and Baharuddin, 2020). The policies also have a positive effect on education; namely, throughout the implementation of the policies, Thai people have increased educational achievements and inequality in this regard has decreased. In addition, it was found that during the period, educational spending declined even if the inequality in this issue was higher. As for healthcare, Thai people spend more on their health after policy implementation, but the disparities in this area have increased (Lindsay *et al.*, 2008). Growing disparities in expenditures, whether in education or healthcare, reflect unequal human capital, which probably affects the quality of such services (Miningou, 2019; Vecchio, Fenech and Prenestini, 2015). Therefore, policymakers should consider how ICT policies can reduce disparities in this area so that Thai people have access to services of the same quality. Moreover, health issues can be viewed in two aspects (Rana, Alam and Gow, 2018). First, Thai people have higher healthcare expenditures because of healthcare information accessibility through ICT devices. Thus it tends to induce more of them to look after their health. Second, using ICT results in more people getting ill and, therefore, more medical expenses.

There is evidence to show gaps between areas, ICT usage patterns and occupations by economic sector. Although the latest ICT policy of Thailand (the Village Broadband Internet) has expanded internet infrastructure to cover all villages across the country, there is still inequality at the area level. Some households still need more access, mainly rural households, because their homes are far from internet access points or poor households with no devices to connect (Thomas, 2017). Therefore, further developments must be accelerated to bridge the gap between urban and rural areas. Considering the statistics on using ICT devices among Thai people, there is a tendency for a decrease in computer usage (Figure 3). The policymakers should be aware of this situation and encourage Thai people to access a wide range of ICT devices to benefit more from ICT policies. For example, in 2003, there was a policy that could assist Thai people in buying computers at low prices, but it has been implemented only for two years. In addition, the agricultural sector should be supported to have greater access and skills to use ICT. While the industrial and service sectors benefit more from the policy, they may need to promote more distributed ICT application skills to reduce inequality within the group (Buchmann, Buchs and Gnehm, 2020).

The impact of ICT policies on inequality in each aspect should be explored in more depth using some mechanisms to elucidate the causes of disparities between groups. Due to differences in areas, there may be issues with the internet coverage rate in each area that affect ICT accessibility (Bhuller, Havnes and Leuven, 2013). However, Internet coverage rate data was one limitation of this study. Another additional work since ICT use in households may affect learning and work skills, and each household likely has different ICT activities. Those skills, therefore, affect the outcomes of occupational groups in each economic sector. Also, regarding the impact on smoking, it is still being determined why ICT use increases tobacco consumption. Further investigation is required on ICT activities or channels of use, which may need to be more effectively appropriate or overused (Civljak *et al.*, 2013; McCrabb *et al.*, 2019; Sung *et al.*, 2013; Salici, 2020). If this further research can delve deeper, it will benefit policymakers to resolve inequality problems or other problems more precisely.

References

Acemoglu, D., Autor, D.H. and Lyle, D. (2004) 'Women, war, and wages: The effect of female labor supply on the wage structure at midcentury', *Journal of political Economy*, 112(3), pp.497-551.

Acemoglu, D. and Restrepo, P. (2020) 'Robots and jobs: Evidence from US labor markets', *Journal of Political Economy*, 128(6) pp. 2188-2244.

Allen, J. P. (2017) *Technology and inequality concentrated wealth in a digital world.* Cham: Palgrave Macmillan.

Araar, A. (2006) *On the decomposition of the Gini coefficient: An exact approach, with an illustration using cameroonian data.* Working Paper 06-02.

Ashenfelter, O. and Card, D. (1985) 'Using the longitudinal structure of earnings to estimate the effect of training programs', *The Review of Economics and Statistics*, 67(4), pp. 648-660.

Athey, S. and Imbens, G. W. (2006) 'Identification and inference in nonlinear difference-in-differences models', *Econometrica*, 74(2), pp.431-497.

Autor, D.H., Levy, F. and Murnane, R.J. (2003) 'Skill demand, inequality, and computerization: Connecting the dots', in Ginther, D.K., Zavodny, M. and Foley L.H. (eds) *Technology, Growth, and the Labor Market.* Springer: Boston. doi.org/10.1007/978-1-4615-0325-5_6.

Bhuller, M., Havnes, T. and Leuven, E. (2013) 'Broadband internet: An information superhighway to sex crime?', *Review of Economic Studies*, 80, pp.1237-1266.

Bleich, S. N. *et al.* (2012) 'Health inequalities: Trends, progress, and policy', *Annual Review of Public Health*, 33, pp.7–40. doi: 10.1146/annurev-publhealth-031811-124658.

Buchmann, M., Buchs, H. and Gnehm, A. S. (2020) 'Occupational inequality in wage returns to employer demand for types of information and communications technology (ICT) skills: 1991–2017', *KZfSS Kölner Zeitschrift für Soziologie und Sozialpsychologie*, 72(1), pp.455-482

Büyükbaykal, C. I. (2015) 'Communication technologies and education in the information age', *Social and Behavioral Sciences*, 174, pp.636-640.

Card, D. and DiNardo, J. E. (2002) 'Skill-biased technological change and rising wage inequality: Some problems and puzzles', *Journal of Labor Economics*, 20(4) pp. 733-783.

Christiansen, A. C. (2001) *Technological change and the role of public policy: An analytical framework for dynamic efficiency assessments.* FNI report.

Civljak, M. *et al.* (2013) 'Internet-based interventions for smoking cessation', *Cochrane Database Syst Rev*, 10(7). doi: 10.1002/14651858.CD007078.pub4.

Coccia, M. (2019) 'What is technology and technology change? A new conception with systemic-purposeful perspective for technology analysis', *Journal of Social and Administrative Sciences*, 6(3), pp.145-169.

Costa, R. N. and Pérez-Duarte, S. (2019) *Not all inequality measures were created equal: The measurement of wealth inequality, its decompositions, and an application to European household wealth.* ECB Statistics Paper Series No 31.

Dagum, C. (1997) 'A new approach to the decomposition of the Gini income inequality ratio', *Empirical Economics*, 22(4), pp. 515-531.

Davino, C., Furno, M. and Victocco, D. (2014) *Quantile regression: Theory and applications.* Sussex: Wiley.

De Maio, F.G. (2007) 'Income inequality measures', *Journal of Epidemiology and Community Health*, 61, pp. 849-852.

Duflo, E. (2001) 'Schooling and labor market consequences of school construction in Indonesia: Evidence from an unusual policy experiment', *American Economic Review*, 91(4), pp. 795-813.

Duplaga, M. (2004) 'The impact of information technology on quality of healthcare services', in Bubak M., *et al.* (eds) *Computational Science - ICCS 2004. Lecture Notes in Computer Science*, 3039. pp.1118–1125. doi: org/10.1007/978-3-540-25944-$2_1$45.

Evenson, R. E. and Westphal, L. E. (1995) 'Technological change and technology strategy', 37, pp. 2209-2299 in Chenery, H. and Srinivasan, T.N. (eds) *Handbook of Development Economics*, 3 (Part 1), Elsevier.

Faggio, G., Salvanes K. G. and Van Reenen J. (2010) 'The evolution of inequality in productivity and wages: Panel data evidence', *Industrial and Corporate Change*, 19(6) pp. 1919–1951. doi: 10.1093/icc/dtq058.

Francesconi, M., Slonimczyk, F. and Yurko, A. (2019) 'Democratizing access to higher education in Russia: The consequences of the unified state exam reform', *European Economic Review*, 117(C), pp. 56-82.

Gupta, H. *et al.* (2016) 'A systematic review of the impact of exposure to internet-based alcohol-related content on young people's alcohol use behaviours', *Alcohol and Alcoholism*, 51(6), pp.763–771. doi: 10.1093/alcalc/agw050.

Godin, B. (2015) *Technological change: What do technology and change stand for? Project on the Intellectual History of Innovation.* Working Paper No. 24.

Havnes, T. and Mogstad, M. (2015) 'Is universal child care leveling the playing field?', *Journal of Public Economics*, 127, pp. 100-114.

Heshmati, A. (2004) *A review of decomposition of income inequality.* IZA Discussion Paper No. 1221.

Hura, G. S. (1998) 'The internet: global information superhighway for the future', *Computer*

Communications, 20, pp. 1412- 1430.

Jacob, B. *et al.* (2016) 'Can technology help promote equality of educational opportunities?', *RSF: The Russell Sage Journal of the Social Sciences*, 2(5), pp. 242-271.

Jing, A.H.Y., Ab-Rahim, R. and Baharuddin, N.N. (2020) 'Information and communication technology (ICT) and income inequality in ASEAN-5 countries', *International Journal of Academic Research in Business and Social Sciences*, 10(1), pp.209-223.

Kalil, T. (1995) 'Public policy and the National Information Infrastructure', *Business Economics*, 30(4), pp. 15-20.

Koenker, R. and Bassett, G. (1978) 'Regression quantiles', *Econometrica*, 46(1), pp. 33-50.

Krueger, A. B. (1993) 'How computers have changed the wage structure: Evidence from microdata, 1984-1989', *The Quarterly Journal of Economics*, 108(1), pp.33-60.

Lerman, R. I. and Yitzhaki, S. (1985) 'Income inequality effects by income source: A new approach and applications to the United States', *The Review of Economics and Statistics*, 67(1), pp. 151-156.

Lindsay, S. *et al.* (2008) 'Enabling healthy choices: is ICT the highway to health improvement?', *Health*, 12(3), pp. 313–331. doi: 10.1177/1363459308090051.

Liu, X. (2010) *Inequality in the Digital World.* All Theses. 766. doi: tigerprints.clemson.edu.

Machin, S., McNally, S. and Silva, O. (2007) 'New technology in schools: Is there a payoff?', *The Economic Journal*, 117(552), pp.1145-1167.

McCrabb, S. *et al.* (2019) 'A cross sectional survey of internet use among a highly socially disadvantaged population of tobacco smokers', *Addict Sci Clin Pract*, 14(38).

Miningou, E. W. (2019) 'Quality education and the efficiency of public expenditure: A cross-country comparative analysis', *World Bank Policy Research.* Working Paper No. 9077.

National Statistical Office of Thailand. (2020) *Socioeconomic Survey (SES).*

NECTEC. (2020) *The Statistics of the Internet user.*

Patria, H. and Erumban, A. A. (2020) 'Impact of ICT adoption on inequality', *JISDeP: The Journal of Indonesia Sustainable Development Planning*, 1(2), pp.125-139.

Rana, R.H., Alam, K. and Gow, J. (2018) 'Development of a richer measure of health outcomes incorporating the impacts of income inequality, ethnic diversity, and ICT development on health', *Globalization and Health*, 14(72). doi.org/10.1186/s12992-018-0385-2.

Rip, A. and Kemp, R. (1997) *Technological change.*

Rothwell, R. and Wissema, H. (1986) 'Technology, culture and public policy', *Technovation*, 4(2), pp. 91-115.

Sánchez-Antolín, P., Ramos, F. J. and Blanco-García, M. (2014) 'Inequality in education and new challenges in the use of information and communication technologies', *Social and Behavioral Sciences*, 116, pp. 1519–1522.

Shorrocks, A. F. (1982) 'Inequality decomposition by factor components', *Econometrica*, 50(1), pp. 193-211.

Shorrocks, A. F. (1982) 'Inequality decomposition by population subgroups', *Econometrica*, 52(6), pp. 1369-1385.

Svensson, R. and Johnson, B. (2020) 'Internet use and adolescent drinking: Does it matter what young people do online?', *Drug and Alcohol Dependence*, 213.

Tchamyou, V. S., Erreygers, G. and Cassimon, D. (2019) 'Inequality, ICT and financial access in Africa', *Technological Forecasting and Social Change*, 139, pp. 169–184. doi: 10.1016/j.techfore.2018.11.004.

Thomas, J. *et al.* (2017) *Measuring Australia's digital divide: The Australian digital inclusion index 2017.* RMIT University, Melbourne, for Telstra.

Van Reenen J. (2011) 'Wage inequality, technology and trade: 21st century evidence', *Labour Economics*, 18 pp.730–741. doi:10.1016/j.labeco.2011.05.006.

Vecchio, M. D., Fenech, L. and Prenestini, A. (2015) 'Private health care expenditure and quality in Beveridge systems: Cross-regional differences in the Italian NHS', *Health Policy*, 119(3), pp. 356-366.

Wagstaff, A. (2002) *Inequalities in Health in Developing Countries: Swimming Against the Tide?.* Policy Research Working Paper No.2795. World Bank, Washington, D.C.

Walker, J. (2019) 'Adding to the list of rural inequalities-Digital technology exclusion', *The Australian Journal of Rural Health*, 27(5), pp.440-441. doi: 10.1111/ajr.12585.

Appendix

Table A1: Variable definitions and summary statistics (1988–2019)

Variable	Definition	Mean	Standard deviation	Minimum	Maximum	No. of households
Dependent Variables						
avg_inc	Monthly income (THB)	22,640.370	45,291.330	-497,437.000	6,032,547.000	78,254
highedu	Highest years of schooling of household member (year)	10.778	3.931	0.000	23.000	78,254
edu_exp	Education expenditure (THB)	338.493	993.713	0.000	65,309.000	78,254
health_exp	Healthcare expenditure (THB)	2,330.473	35,293.180	0.000	1,340,014.000	78,254
alcohol	Alcohol consumption (THB)	97.603	411.710	0.000	64,500.000	78,254
smoking	Tobacco consumption (THB)	74.131	358.298	0.000	85,785.000	78,254
Explanatory Variables						
reg_ict	ICT penetration rate by region (ratio)	0.594	0.402	0.000	0.987	78,254
prov_ict	ICT penetration rate by province (ratio)	0.593	0.404	0.000	1.000	78,254
gender	Dummy variable that equals to 1 if household member who earns highest income is male and 0 if others	0.468	0.4999	0.000	1.000	78,254
age	Age of household member who earns highest income (year)	31.245	12.474	13.000	80.000	78,254
member	Number of household member (people)	5.282	1.421	3.000	23.000	78,254
avg_exp	Monthly expenditure (THB)	17,261.650	16,138.440	749.000	508,070.000	78,254
dependency	Dependency ratio (%)	104.167	83.785	0.000	800.000	78,254
gen_y	Dummy variable that equals to 1 if the youngest household member is male and 0 if others	0.520	0.500	0.000	1.000	78,254
age_y	Age of youngest household member (year)	6.817	6.253	0.000	62.000	78,254
yratio	Proportion of young household members to all (ratio)	0.265	0.138	0.000	0.830	78,254
gen_o	Dummy variable that equals to 1 if the oldest household member is male and 0 if others	0.515	0.500	0.000	1.000	78,254
age_o	Age of oldest household member (year)	65.280	11.258	27.000	99.000	78,254
oratio	Proportion of old household members to all (ratio)	0.181	0.148	0.000	1.000	78,254

Table A2: Balance test

Variables	Whole sample	Used sample	Pre-intervention	Post-intervention	Difference
	(a)	(b)	(c)	(d)	(d)-(c)
Dependent Variables					
avg_inc	19,359.965	22,640.371	11,240.479	27,296.243	16,055.764***
highedu	9.623	10.778	9.271	11.393	2.122***
edu_exp	257.564	338.493	171.963	406.506	234.543***
health_exp	1,252.884	2,330.473	356.386	3,136.717	2,780.331***
alcohol	94.834	97.603	152.831	75.048	-77.783***
smoking	57.052	74.131	136.967	48.468	-88,499***
Explanatory Variables					
reg_ict	0.639	0.594	0.012	0.832	0.820***
prov_ict	0.639	0.593	0.012	0.831	0.819***
gender	0.556	0.468	0.514	0.450	-0.064***
age	38.140	31.245	28.257	32.466	4.209***
member	3.230	5.282	5.525	5.183	-0.342***
avg_exp	14,734.583	17,261.649	8,630.408	20,786.767	12,156.359***
dependency	61.278	104.167	105.805	103.498	-2.307***
gen_y	0.463	0.520	0.520	0.520	0.000
age_y	24.0887	6.817	5.810	7.228	1.418***
yratio	0.169	0.265	0.283	0.257	-0.026***
gen_o	0.612	0.515	0.531	0.5080	-0.023***
age_o	53.378	65.280	64.211	65.717	1.506***
oratio	0.186	0.181	0.165	0.187	0.022***

Notes: $***$, $**$ and $*$ denote statistical significance at the 1%, 5% and 10% significance levels, respectively.

Table A3: Effect of ICT policies on earnings

	DiD	Quantile DiD				
		τ=0.10	τ=0.25	τ=0.50	τ=0.75	τ=0.90
Panel A Labour force						
−**Monthly income:** *lnavg_inc*						
reg_ict	0.150**	0.165	0.168**	0.186**	0.153**	0.191*
	(0.061)	(0.122)	(0.066)	(0.050)	(0.075)	(0.106)
gender	-0.005	-0.013**	-0.005	-0.001	0.002	-0.002
	(0.003)	(0.006)	(0.004)	(0.003)	(0.004)	(0.006)
age	0.005***	0.005***	0.004***	0.004***	0.005***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
member	0.019***	0.026***	0.019***	0.017***	0.017***	0.018***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
highedu	0.032***	0.036***	0.030***	0.026***	0.030***	0.032***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
lnavg_exp	0.836***	0.761***	0.848***	0.882***	0.872***	0.869***
	(0.004)	(0.006)	(0.004)	(0.005)	(0.004)	(0.005)
dependencey	-0.0002***	-0.0001***	-0.0002***	-0.0002***	-0.0003***	-0.0003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$R^2/PseudoR^2$	0.762	0.518	0.553	0.559	0.533	0.489
Observations	78,254	78,254	78,254	78,254	78,254	78,254
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each pair of rows reports the coefficient estimate and the associated standard error in parenthesis. $***$, $**$ and $*$ denote statistical significance at the 1%, 5% and 10% significance levels, respectively.

Table A4: Effect of ICT policies on education

	DiD	Quantile DiD				
		τ=0.10	τ=0.25	τ=0.50	τ=0.75	τ=0.90
Panel B Education						
−**Years of schooling:** *highedu*						
reg_ict	0.799***	-0.745	-0.017	0.892*	1.901***	1.222*
	(0.463)	(0.600)	(0.478)	(0.539)	(0.678)	(0.710)
gender	-0.377***	-0.254***	-0.322***	0.006***	-0.438***	-0.403***
	(0.022)	(0.025)	(0.021)	(-0.170)	(0.024)	(0.030)
age	-0.003***	-0.037***	-0.019***	1.631***	0.018***	0.023***
	(0.001)	(0.001)	(0.001)	(2.283)	(0.002)	(0.002)
member	-0.153***	-0.002	-0.088***	-0.004***	-0.218***	-0.186***
	(0.008)	(0.010)	(0.012)	(0.892)	(0.009)	(0.011)
lnavg_inc	1.466***	0.764***	1.219***	-0.413***	1.638***	1.301***
	(0.026)	(0.031)	(0.034)	(0.006)	(0.038)	(0.027)
lnavg_exp	2.050***	1.406***	2.105***	-0.170***	2.029***	1.409***
	(0.033)	(0.040)	(0.043)	(1.631)	(0.041)	(0.035)
dependencey	-0.003***	-0.004***	-0.005***	2.283***	-0.002***	-0.001***
	(0.000)	(0.000)	(0.000)	(-0.004)	(0.000)	(0.000)
$R^2/PseudoR^2$	0.398	0.156	0.213	0.278	0.271	0.150
Observations	78,254	78,254	78,254	78,254	78,254	78,254
−**Education expenditure:** *lnedu_exp*						
reg_ict	-0.996***	-0.262	-0.915***	-1.021***	-0.986***	-0.671**
	(0.175)	(0.287)	(0.319)	(0.265)	(0.275)	(0.275)
gen_y	-0.026***	-0.015	-0.015	-0.028*	-0.017	-0.022
	(0.010)	(0.020)	(0.016)	(0.014)	(0.014)	(0.015)
age_y	0.073***	0.109***	0.099***	0.073***	0.050***	0.042***
	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
yratio	0.904***	1.820***	1.422***	0.845***	0.617***	0.566***
	(0.058)	(0.099)	(0.089)	(0.076)	(0.079)	(0.086)
lnavg_inc	0.481***	0.339***	0.411***	0.482***	0.485***	0.501***
	(0.008)	(0.013)	(0.013)	(0.011)	(0.013)	(0.014)
highedu	0.108***	0.061***	0.082***	0.119***	0.141***	0.143***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)
dependency	0.0002***	-0.00003	0.0001	0.0003***	0.0002*	0.0003**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$R^2/PseudoR^2$	0.334	0.137	0.155	0.198	0.250	0.272
Observations	58,503	58,503	58,503	58,503	58,503	58,503
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each pair of rows reports the coefficient estimate and the associated standard error in parenthesis. $***$, $**$ and $*$ denote statistical significance at the 1%, 5% and 10% significance levels, respectively.

Table A5: Effect of ICT policies on Healthcare

	DiD	Quantile DiD				
		τ=0.10	τ=0.25	τ=0.50	τ=0.75	τ=0.90
Panel C Healthcare						
−**Healthcare expenditure:** *lnhealth_exp*						
reg_ict	0.399*	0.291	0.029	0.349	0.631***	0.381
	(0.227)	(0.436)	(0.365)	(0.356)	(0.177)	(0.319)
age_y	-0.022***	-0.014***	-0.021***	-0.022***	-0.020***	-0.017***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
age_o	0.003***	0.003***	0.003***	0.003***	0.004***	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
oratio	0.620***	0.227***	0.370***	0.596***	0.729***	0.854***
	(0.076)	(0.086)	(0.068)	(0.082)	(0.097)	(0.154)
lnavg_inc	0.637***	0.421***	0.580***	0.665***	0.666***	0.745***
(0.009)	(0.014)	(0.013)	(0.014)	(0.012)	(0.016)	
dependency	-0.0004***	-0.0002	-0.0002*	-0.0004***	-0.0004***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$R^2/PseudoR^2$	0.135	0.054	0.069	0.078	0.087	0.095
Observations	56,301	56,301	56,301	56,301	56,301	56,301
−**Alcohol consumption:** *lnalcohol*						
reg_ict	0.005	0.373	-0.065	-0.126	0.446	-0.598
	(0.221)	(0.482)	(0.339)	(0.297)	(0.300)	(0.372)
member	-0.001	0.001	0.001	0.003	-0.002	-0.010
	(0.005)	(0.008)	(0.005)	(0.005)	(0.006)	(0.008)
highedu	0.014***	0.014***	0.012***	0.012***	0.013***	0.014***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
lnavg_inc	0.427***	0.373***	0.405***	0.433***	0.454***	0.472***
	(0.011)	(0.016)	(0.012)	(0.016)	(0.015)	(0.020)
dependency	-0.0002***	-0.0002	-0.0003**	-0.0003**	-0.0003***	-0.0001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$R^2/PseudoR^2$	0.376	0.189	0.202	0.217	0.226	0.232
Observations	19,376	19,376	19,376	19,376	19,376	19,376
−**Tobacco consumption:** *lnsmoking*						
reg_ict	0.804***	0.439**	0.645*	1.078***	1.289***	1.010***
	(0.210)	(0.223)	(0.339)	(0.263)	(0.333)	(0.339)
member	0.014***	0.022***	0.023***	0.017***	0.008	0.009
	(0.004)	(0.008)	(0.006)	(0.008)	(0.005)	(0.008)
highedu	0.026***	0.016***	0.027***	0.032***	0.025***	0.016***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
lnavg_inc	0.493***	0.273***	0.440***	0.548***	0.558***	0.512***
	(0.010)	(0.020)	(0.018)	(0.012)	(0.015)	(0.019)
dependency -0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$R^2/PseudoR^2$	0.394	0.231	0.242	0.236	0.229	0.211
Observations	33,404	33,404	33,404	33,404	33,404	33,404
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each pair of rows reports the coefficient estimate and the associated standard error in parenthesis. $***$, $**$ and $*$ denote statistical significance at the 1%, 5% and 10% significance levels, respectively.

Table A6: Effect of ICT policies on outcomes in different household attributes (by area)

	Panel A Labour force	**Panel B Education**		**Panel C Healthcare**		
	Earnings	**Years of schooling**	**Education expenditure**	**Healthcare expenditure**	**Alcohol consumption**	**Smoking**
reg_ict × municipal area	0.028***	0.797***	0.207***	0.082***	0.109***	0.354***
	(0.004)	(0.031)	(0.015)	(0.020)	(0.018)	(0.020)
gender	-0.005	-0.373***				
	(0.004)	(0.022)				
age	0.004***	-0.004***				
	(0.000)	(0.001)				
member	0.020***	-0.142***			-0.0005	0.017***
	(0.001)	(0.008)			(0.005)	(0.004)
highedu	0.032***		0.105***		0.013***	0.023***
	(0.001)		(0.001)		(0.002)	(0.002)
avg_inc		1.442***	0.471***	0.632***	0.422***	0.481***
		(0.031)	(0.008)	(0.009)	(0.011)	(0.010)
avg_exp	0.835***	2.005***				
	(0.004)	(0.033)				
dependency	-0.0002***	-0.003	0.0002***	-0.0004***	-0.0002***	-0.001***
	(0.004)	(0.000)	(0.000)	(0.0001)	(0.000)	(0.000)
gen_y			-0.026***			
			(0.010)			
age_y			0.072***	-0.022***		
			(0.001)	(0.001)		
age_o				0.003***		
				(0.001)		
yratio			0.889***			
			(0.058)			
oratio				0.619***		
				(0.076)		
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.762	0.403	0.336	0.135	0.378	0.400
Observations	78,254	78,254	58,503	56,301	19,376	33,404

Notes: Each pair of rows reports the coefficient estimate and the associated standard error in parenthesis. $***$, $**$ and $*$ denote statistical significance at the 1%, 5% and 10% significance levels, respectively.

Table A7: Effect of ICT policies on outcomes in different household attributes (by ICT using)

	Panel A Labour force	Panel B Education		Panel C Healthcare		
	Earnings	**Years of schooling**	**Education expenditure**	**Healthcare expenditure**	**Alcohol consumption**	**Smoking**
reg_ict × multimodal user	0.085***	1.529***	0.719***	0.303***	-0.008	0.301***
	(0.007)	(0.040)	(0.023)	(0.031)	(0.029)	(0.038)
gender	-0.005	-0.370***				
	(0.004)	(0.022)				
age	0.006***	-0.004***				
	(0.000)	(0.001)				
member	0.020***	-0.135***			-0.001	0.016***
	(0.001)	(0.008)			(0.004)	(0.004)
highedu	0.032***		0.099***		0.014***	0.024***
	(0.001)		(0.002)		(0.002)	(0.002)
avg_inc		1.410***	0.427***	0.610***	0.427***	0.482***
		(0.026)	(0.008)	(0.009)	(0.011)	(0.010)
avg_exp	0.828***	1.901***				
	(0.004)	(0.033)				
dependency	-0.0002***	-0.003	0.0002***	-0.0004***	-0.0002***	-0.001***
	(0.000)	(0.0001)	(0.000)	(0.0001)	(0.000)	(0.000)
gen_y			-0.028***			
			(0.010)			
age_y			0.069***	-0.023***		
			(0.001)	(0.001)		
age_o				0.003***		
				(0.001)		
yratio			0.897***			
			(0.057)			
oratio				0.613***		
				(0.076)		
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.762	0.407	0.349	0.137	0.376	0.395
Observations	78,254	78,254	58,503	56,301	19,376	33,404

Notes: Each pair of rows reports the coefficient estimate and the associated standard error in parenthesis. $***$, $**$ and $*$ denote statistical significance at the 1%, 5% and 10% significance levels, respectively.

Table A8: Effect of ICT policies on outcomes in different household attributes (by occupational patterns)

	Panel A Labour force	**Panel B Education**		**Panel C Healthcare**		
	Earnings	**Years of schooling**	**Education expenditure**	**Healthcare expenditure**	**Alcohol consumption**	**Smoking**
reg_ict × agricultural sector	-0.114***	-1.295***	-0.355***	-0.056***	-0.081***	-0.297***
	(0.006)	(0.039)	(0.018)	(0.024)	(0.022)	(0.022)
gender	-0.002	-0.333***				
	(0.003)	(0.022)				
age	0.005***	-0.0001				
	(0.000)	(0.001)				
member	0.021***	-0.136***			-0.0008	0.016***
	(0.001)	(0.008)			(0.005)	(0.004)
highedu	0.031***		0.103***		0.013***	0.023***
	(0.001)		(0.002)		(0.002)	(0.002)
avg_inc		1.390***	0.465***	0.632***	0.423***	0.480***
		(0.026)	(0.008)	(0.009)	(0.011)	(0.010)
avg_exp	0.829***	1.995***				
	(0.004)	(0.032)				
dependency	-0.0002***	-0.003	0.0002***	-0.0004***	-0.0002***	-0.001***
	(0.000)	(0.0001)	(0.000)	(0.0001)	(0.000)	(0.000)
gen_y			-0.026***			
			(0.010)			
age_y			0.072***	-0.022***		
			(0.001)	(0.001)		
age_o				0.003***		
				(0.001)		
yratio			0.887***			
			(0.058)			
oratio				0.634***		
				(0.009)		
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.763	0.407	0.339	0.135	0.377	0.397
Observations	78,254	78,254	58,503	56,301	19,376	33,404

Notes: Each pair of rows reports the coefficient estimate and the associated standard error in parenthesis. $***$, $**$ and $*$ denote statistical significance at the 1%, 5% and 10% significance levels, respectively.

Table A9: Effect of ICT policies on inequality, by area

	Non-municipal area				**Municipal area**			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Panel A Labour force: Earnings								
prov_ict	0.006	0.007	-0.135***	-0.010	0.001	0.003	-0.250***	0.007
	(0.006)	(0.006)	(0.051)	(0.063)	(0.007)	(0.006)	(0.049)	
(0.067) R^2	0.001	0.001	0.074	0.070	0.001	0.000	0.127	0.113
Observations	1,267	1,267	1,267	1,267	1,282	1,282	1,282	1,282
Panel B Education: Years of Schooling								
prov_ict	-0.017***	-0.016***	-0.093***	-0.084***	-0.040***	-0.039***	-0.146***	-0.056**
	(0.002)	(0.002)	(0.019)	(0.025)	(0.003)	(0.003)	(0.022)	(0.026)
R^2	0.035	0.035	0.223	0.223	0.145	0.149	0.293	0.284
Observations	1,267	1,267	1,267	1,267	1,282	1,282	1,282	1,282
Educational expenditure								
prov_ict	0.127***	0.127***	-0.006	-0.059	0.158***	0.157***	-0.075	-0.051
	(0.008)	(0.007)	(0.073)	(0.087)	(0.009)	(0.008)	(0.057)	(0.086)
R^2	0.165	0.165	0.243	0.243	0.214	0.214	0.325	0.325
Observations	1,262	1,262	1,262	1,262	1,281	1,281	1,281	1,281
Panel C Healthcare: Healthcare expenditure								
prov_ict	0.083***	0.084***	-0.049	-0.042	0.117***	0.119***	0.097	0.276***
	(0.011)	(0.009)	(0.083)	(0.100)	(0.009)	(0.010)	(0.092)	(0.100)
R^2	0.055	0.055	0.243	0.243	0.093	0.093	0.275	0.273
Observations	1,267	1,267	1,267	1,267	1,278	1,278	1,278	1,278
Province FE	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	No	No	Yes	Yes	No	Yes	No	Yes

Notes: Each pair of rows reports the coefficient estimate and the associated standard error in parenthesis. $***$, $**$ and $*$ denote statistical significance at the 1%, 5% and 10% significance levels, respectively.

Table A10: Effect of ICT policies on inequality, by economic sector

	Agriculture				**Industry**				**Service**			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Panel A Labour force: Earnings												
prov_ict	0.017**	0.014*	-0.260***	-0.034	0.061***	0.057***	0.178**	-0.007	-0.013**	-0.011**	-0.206***	0.029
	(0.008)	(0.007)	(0.093)	(0.089)	(0.009)	(0.008)	(0.082)	(0.096)	(0.006)	(0.006)	(0.041)	(0.060)
R^2	0.003	0.003	0.050	0.046	0.035	0.035	0.100	0.096	0.004	0.004	0.116	0.102
Observations	1,257	1,257	1,257	1,257	1,162	1,162	1,162	1,162	1,286	1,286	1,286	1,286
Panel B Education: Years of Schooling												
prov_ict	0.008**	0.007*	-0.151***	-0.019	0.025***	0.023***	0.063	-0.036	-0.044***	-0.043***	-0.128***	-0.052**
	(0.004)	(0.003)	(0.053)	(0.039)	(0.005)	(0.005)	(0.045)	(0.050)	(0.002)	(0.002)	(0.019)	(0.023)
R^2	0.003	0.003	0.088	0.077	0.020	0.020	0.137	0.133	0.214	0.214	0.359	0.351
Observations	1,257	1,257	1,257	1,257	1,162	1,162	1,162	1,162	1,286	1,286	1,286	1,286
Educational expenditure												
prov_ict	0.147***	0.142***	-0.406***	-0.076	0.213***	0.215***	0.676***	0.249*	0.129***	0.128***	-0.003	-0.047
	(0.012)	(0.011)	(0.128)	(0.121)	(0.016)	(0.014)	(0.122)	(0.149)	(0.007)	(0.007)	(0.048)	(0.073)
R^2	0.116	0.116	0.185	0.179	0.143	0.143	0.183	0.174	0.212	0.212	0.280	0.280
Observations	1,225	1,225	1,225	1,225	1,067	1,067	1,067	1,067	1,285	1,285	1,285	1,285
Panel C Healthcare: Healthcare expenditure												
prov_ict	0.019	0.012	-0.587***	0.037	0.152***	0.139***	0.627***	0.022	0.108***	0.109***	0.038	0.152*
	(0.014)	(0.011)	(0.192)	(0.138)	(0.017)	(0.015)	(0.125)	(0.165)	(0.009)	(0.009)	(0.071)	(0.089)
R^2	0.002	0.002	0.066	0.046	0.066	0.066	0.127	0.113	0.098	0.098	0.308	0.307
Observations	1,234	1,234	1,234	1,234	1,116	1,116	1,116	1,116	1,285	1,285	1,285	1,285
Province FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	No	No	Yes	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Notes: Each pair of rows reports the coefficient estimate and the associated standard error in parenthesis. $***$, $**$ and $*$ denote statistical significance at the 1%, 5% and 10% significance levels, respectively.