The Impact of Technological Change on Inequality, Health and Crime: Evidence from Thailand

Ariya Phaokrueng

A thesis submitted for the degree of

Doctor of Philosophy

Department of Economics

University of Essex

April 2024

Summary

In most developing countries, technological advancements have occurred rapidly in recent years. These economies emphasise technological changes contributing to their economic growth, especially information and communication technology (ICT). ICT policies have been launched since 2001 to improve Thai people's quality of life. ICT has several benefits for both the economy and society. However, it can also have adverse effects.

One of the Thai government's goals is to reduce inequality using ICT policies. The first chapter evaluates the impact of technology policy on inequality from different perspectives, including labour force, education, and healthcare. Results prove that ICT policies increase earnings and improve educational achievements. Such inequality has decreased. However, expenditure disparities in education and healthcare persist, and more healthcare investments exist.

Whether the increased healthcare expenditures are due to increased access to healthcare information via ICT or increased morbidity remains questionable. The second chapter investigates and quantifies the impact of ICT usage behaviour on physical and mental health problems. The findings imply that Thai people are more likely to have some health problems from ICT use. ICT adoption at different times begins to affect health at various times and has different likelihood of illnesses. The effects on mental health occur faster than physical health. Time spent on ICT affects physical health, while some ICT activities, such as learning, social media, and entertainment, impact both physical and mental health.

Another issue that could be a consequence of ICT is crime. Certain ICT activities, such as social media, have risks that could lead to crime. However, ICT is also an effective tool for deterring crime. Chapter 3 results reveal that social media has decreased reported crime rates while increasing convicted crime rates. Fraud and prostitution are the most concerning forms of crime, possibly stimulated by social media.

To my beloved father, *Subin Phaokrueng*.

Acknowledgements

"...It's not the journey that counts, but who is at your side..." Arikawa (2019)

This sentence reflects my feelings about the PhD journey. Although it has had some difficult moments, everything has always worked well, thanks to the support of many benefactors.

I wish to express my sincere gratitude to my supervisors, Professor Marco Francesconi and Dr Xiaoyu Xia, for providing invaluable guidance and encouragement throughout my PhD experience. I acknowledge the Royal Thai Government's financial support during my PhD studentship.

I am immensely grateful to Sukanya Huayhongthong, staff of the National Statistical Office of Thailand (NSO), for advising, coordinating and facilitating all the data used in this thesis. I have benefited from discussions about data fusion techniques with Associate Professor Akarapong Untong, Dr Natthapon Anantanasan, and Dr Theerayuth Phiriyaarayakul. I also thank Police Colonel Chatikorn Srimuang for helpful discussions on interpreting crime results.

Thanks to all my friends and colleagues who made this PhD journey more meaningful and all the seminar and conference participants for their questions and feedback.

Last but not least, I am deeply indebted to my family, especially my mother and husband, for their constant support and love. I could not have succeeded in this challenge without them. All the errors and mistakes are my own.

Contents

List of Tables

List of Figures

Chapter 1

Evolution of ICT Policy, Accessibility and Impact on Inequality

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

I wish to thank Professor Marco Francesconi and Dr Xiaoyu Xia for their valuable guidance and seminar participants at the University of Essex and the Tenth ECINEQ Meeting for helpful comments and suggestions.

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.

1.1 Introduction

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 information and communication technology (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.

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. The ratio of ICT penetration by region is the treatment indicator of the identification strategy, with households living in higher ICT access regions identified as the treatment group and comparable households living in lower ICT access regions identified as the control group. Therefore, this strategy exploits the variation in treatment across groups of units at different times.

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. 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-municipal ones. 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. 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.

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.

1.2 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.

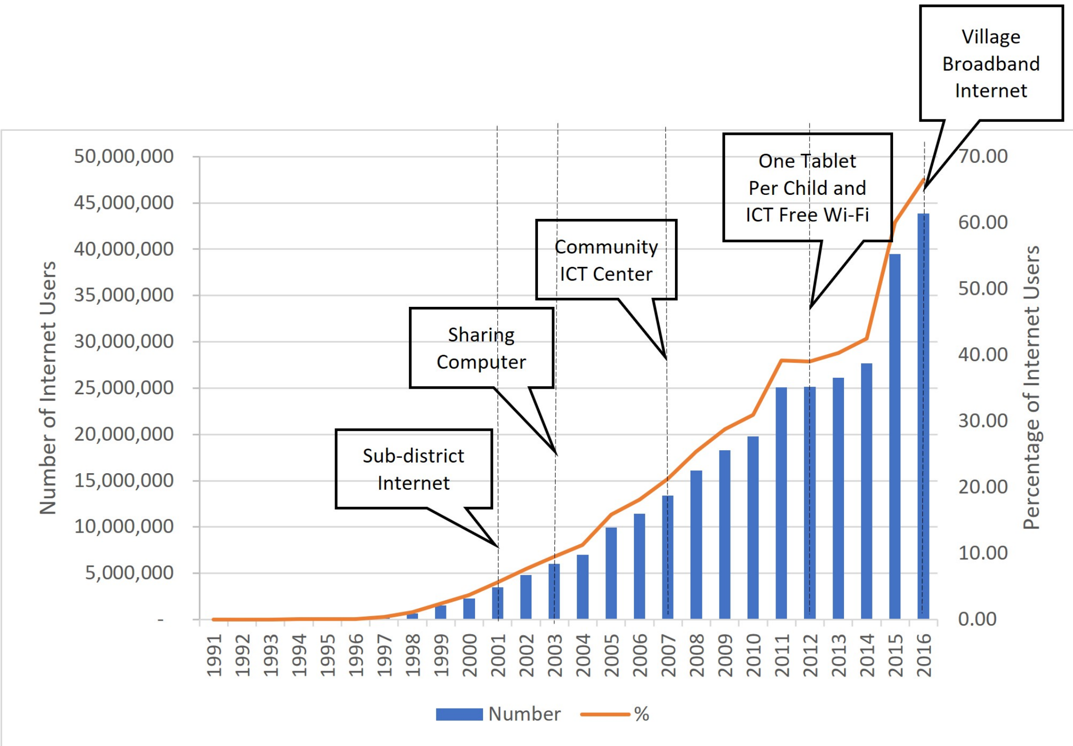
ICT has become a necessity for healthcare. However, what happens to people being left behind or abandoned by this technological revolution, as the internet is increasingly used to communicate health knowledge, and there is a growing belief that it can help transform personal and public health? Lindsay *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.

1.3 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 1.1 clearly reflects the result of ICT policies due to the continuously increasing trend of internet users.

Figure 1.1: 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.

1.3.1 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.1.1.

The potential outcomes employed in this study, 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.1.2 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 1.2. 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%.

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 1.3(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 1.3(ii) indicates a relatively high ICT concentration in Bangkok until 2012, when it 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 1.4. Prior to the initiation of the ICT policy, households with access to ICT were high-income, high-educated, and high-healthcare

Figure 1.2: Percentage of households with ICT devices, 1988-2019

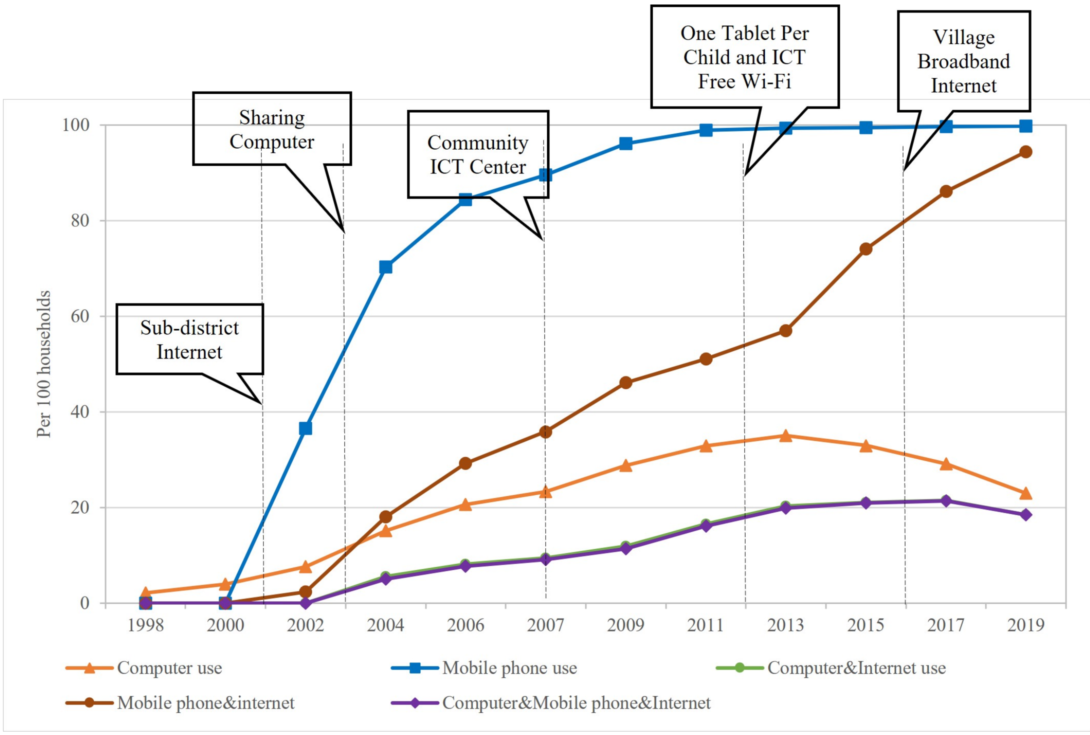
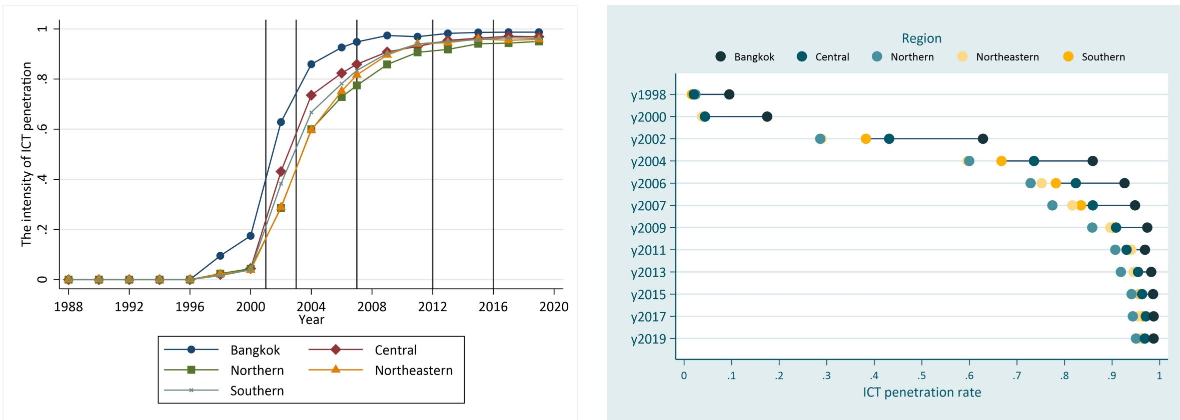


Figure 1.3: The ICT penetration rate by region, 1988 – 2019

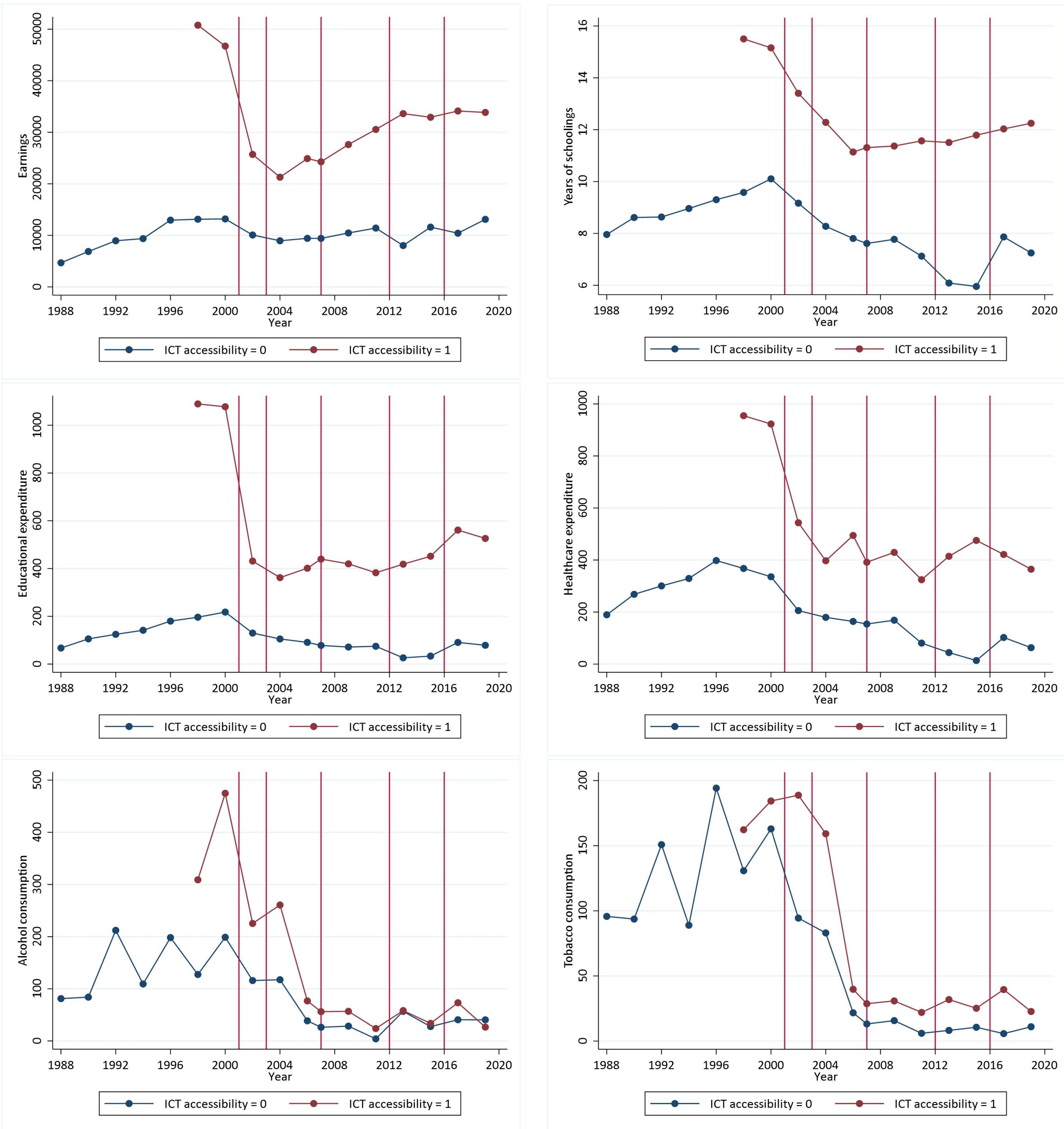


(i) (ii)

Notes: The vertical grey lines in the left figure indicate each ICT policy implementation.

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 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.

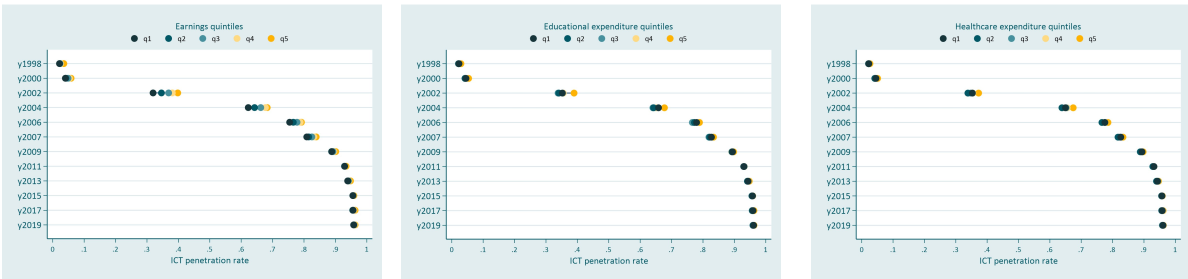
Figure 1.4: Household comparison with ICT accessibility in each outcome, 1988-2019



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

In the inequality analysis, differences in outcomes are considered by quintiles. Figure 1.5 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.

Figure 1.5: The intensity of ICT penetration by outcomes quintiles: earnings, educational expenditure and healthcare expenditure, 1998 - 2019

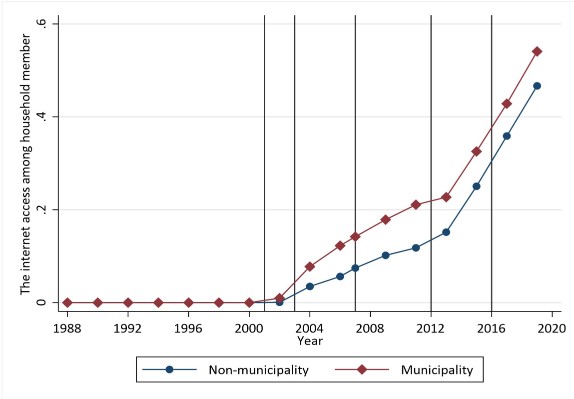


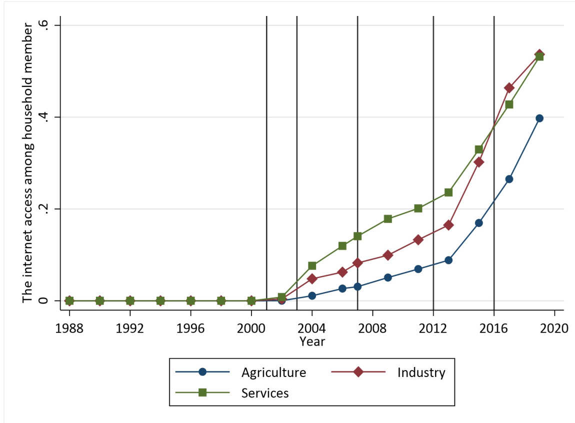
The proportion of household members with internet access classified by household characteristics is shown in Figure 1.6. In the early stages of the ICT policy, there was an increasing gap between household members' access to the internet in municipal and non-municipal areas. However, the gap narrowed 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.

1.3.2 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

Figure 1.6: 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.

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. The assessment of the technology policy's impact on potential outcomes can be extended to a generalized framework, facilitating estimation of the following Difference-in-Differences (DD) model for all outcome variables included in the main baseline specification:

$$y_{irt} = \alpha + \beta_r + \gamma_t + \delta Treat_{rt} + \omega X'_{irt} + \varepsilon_{irt} \tag{1.1}$$

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; Adorno, Bernini and Pellegrini, 2007).

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.

$$y_{irt}^{(\tau)} = \alpha^{(\tau)} + \beta_r^{(\tau)} + \gamma_t^{(\tau)} + \delta^{(\tau)} Treat_{rt} + \omega^{(\tau)} X'_{irt} + \varepsilon_{irt} \tag{1.2}$$

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 reflects province characteristics, including area and economic sector.

The next step involves utilizing the Gini coefficient as an additional potential outcome to assess the impact of the technology policy. This application extends the difference-in-differences model to the following specification:

$$y_{pt} = \alpha + \beta_p + \gamma_t + \delta Treat_{pt} + \varepsilon_{pt} \tag{1.3}$$

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), and ε_{pt} is a residual disturbance.

For endogeneity concerns, the econometric techniques used to address endogeneity problems in this study can be discussed by classification into two parts. The first part includes techniques for identifying the coefficients of interest that rely on a clear source of exogenous variation, i.e., difference-in-differences estimators. Apart from the DiD method being an appropriate tool to evaluate the effect of policy, its effectiveness depends on the randomness of the policy variables, which requires defining a natural experiment or quasi-experiment (Li *et al.*, 2021). One way to estimate the parameters that summarize treatment outcomes was to compare the post-intervention outcomes of the households in the treatment and control groups. The cross-sectional comparisons avoid the problem of omitted trends by comparing two groups over the same period. A second way of estimating treatment outcomes was to compare post-intervention outcomes with pre-intervention outcomes for treated households only. Such time series comparison avoids the problem of unobserved differences between two different groups of households by looking at the same households before and after the change. As a result, the two single difference estimators complement each other. The DiD estimator combines these two estimators to take advantage of the strengths of both estimators (Roberts and Whited, 2013). Therefore, the DiD method can solve the endogeneity issues to a certain extent.

The second part includes techniques that rely on modeling assumptions i.e., fixed effects. They are easy to implement and effective in controlling for time invariant omitted variables (Li *et al.*, 2021). The two-way fixed-effect (TWFE) model can rule out various concerns (Braghieri, Levy and Makarin, 2022). First, the results are driven by time-invariant differences in each outcome across regions. Specifically, one could worry that more selective regions of higher ICT access households may have better (or worse) baseline outcomes. By including region fixed effect, such concerns can be ruled out. Second, the results are driven by each outcome evolving over time in a way that is common across households in different regions. For example, certain economic fluctuations might influence all households' prospects in a similar way and affect their outcomes. Year fixed effects can rule out such concerns as well. To conclude, fixed effects can ameliorate endogeneity concerns. Hence, the identification strategies in this study can still be valid.

1.4 Empirical Findings

1.4.1 Household Level

The results in Tables 1.1-1.3 are based on equations (1.1) and (1.2) 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 1.1 and Appendix Table A1.3, 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 1.1: 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 1.2 (see more results in AppendiX Table A1.4) 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 1.3 and Appendix Table A1.5 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

Table 1.2: 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.

(*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.

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 (as shown in Table 1.4). The previous empirical results based on the overall sample may not incorporate household differences with loca-

Table 1.3: 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.

tions, ICT usage patterns and occupation in economic sectors.

Regarding household location, they considered households in municipal areas 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 1.2. According to the study of these usage differences, multimodal users benefit from the ICT policies more in outcomes than other users. This can be noticed 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 1.4: Effect of ICT policies on outcomes in different household attributes

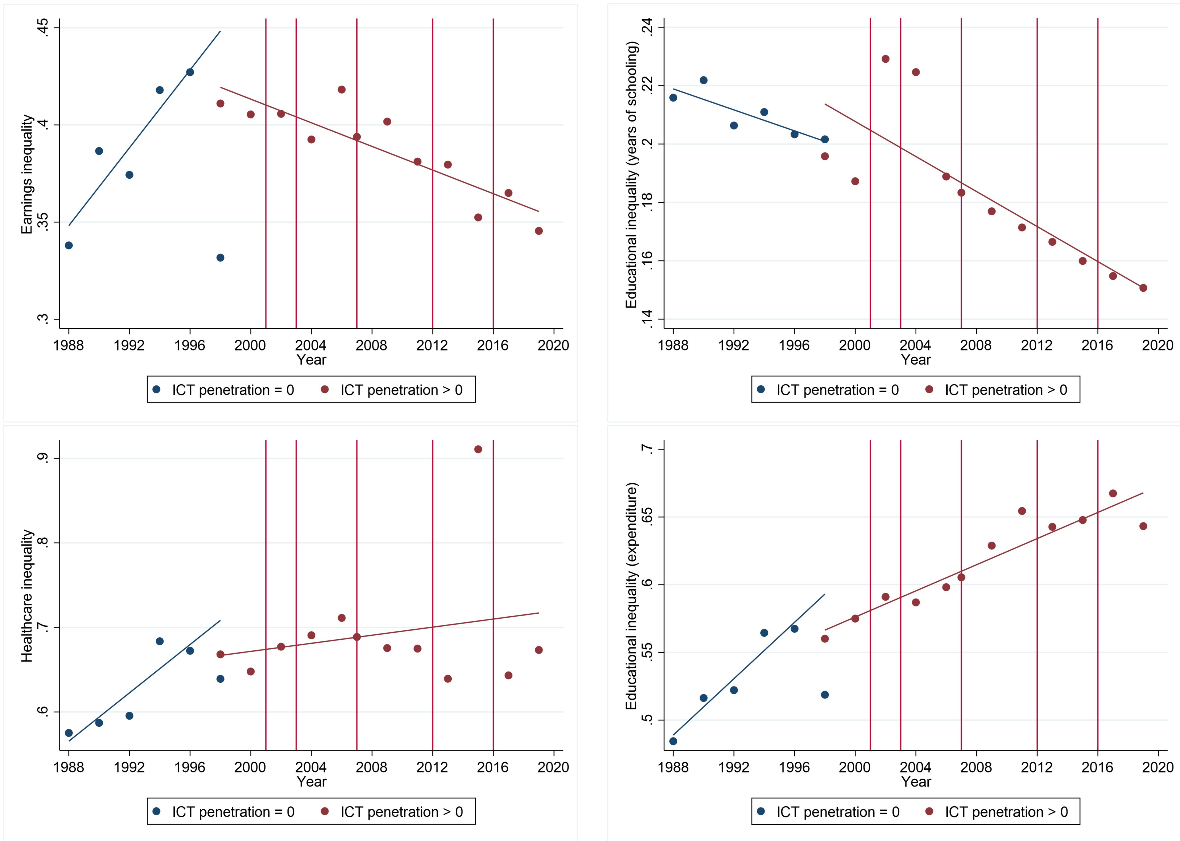
	Panel A Labour force	**Panel B Education**		**Panel C Healthcare**		
	Earnings	**Years of schooling**	**Education expenditure**	**Healthcare expenditure**	**Alcohol consumption**	**Smoking**
reg_ict × municipal area	0.028***	0.797***	0.207***	0.082***	0.109***	0.354***
	(0.004)	(0.031)	(0.015)	(0.020)	(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.

1.4.2 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 1.7, 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 1.7: 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 1.5 displays the estimated equation (1.3) results 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 household data analysis shows that ICT policies have increased the distribution of some outcomes at different levels, it is still being determined whether inequality has increased.

Table 1.5: 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.

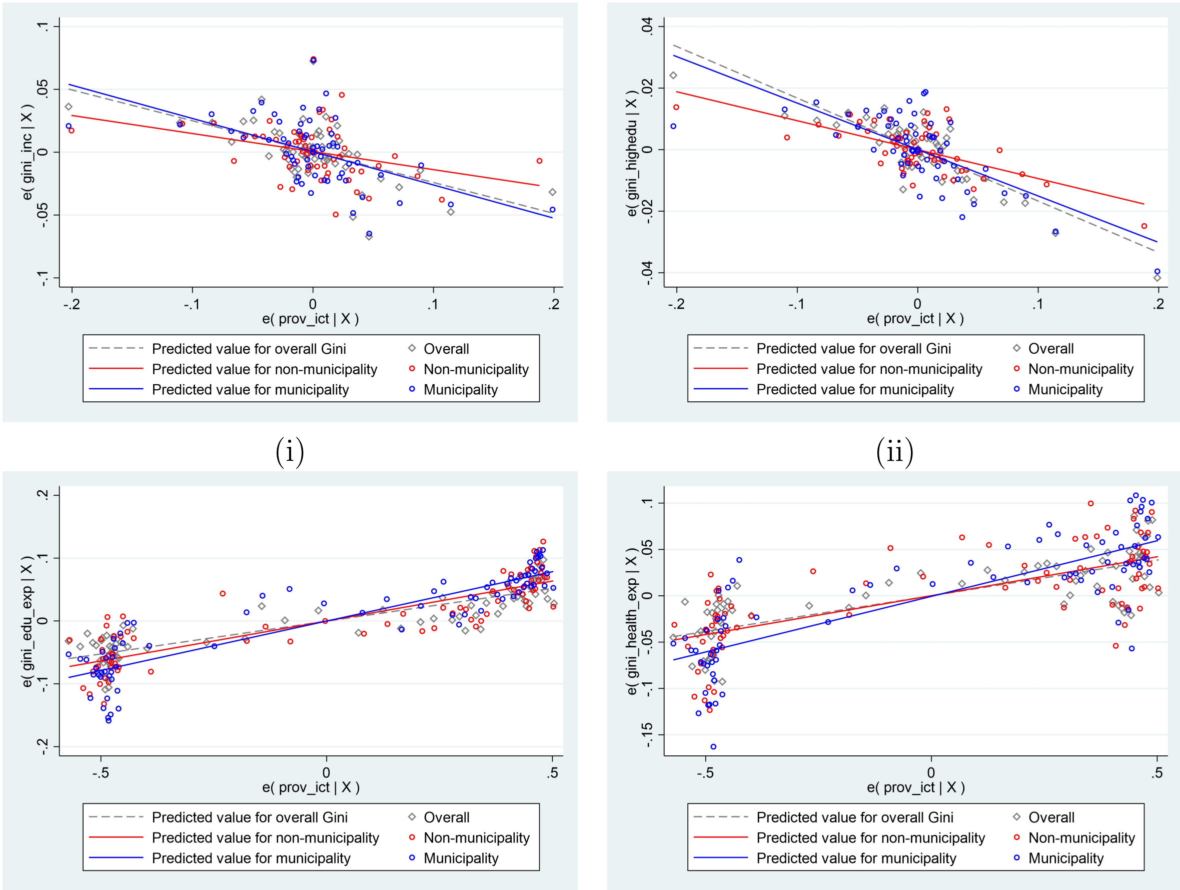
Decomposition analysis

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 A1.9. The yield coefficients of the municipality coefficients were higher than those in the non-municipal coefficient models.

Figure 1.8 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, they could reap more benefits from ICT policies. This is consistent with the previous study on household-level data.

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 A1.10, 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

Figure 1.8: Association between Gini coefficient and ICT penetration, by area



(i) (ii) (iii) (iv)

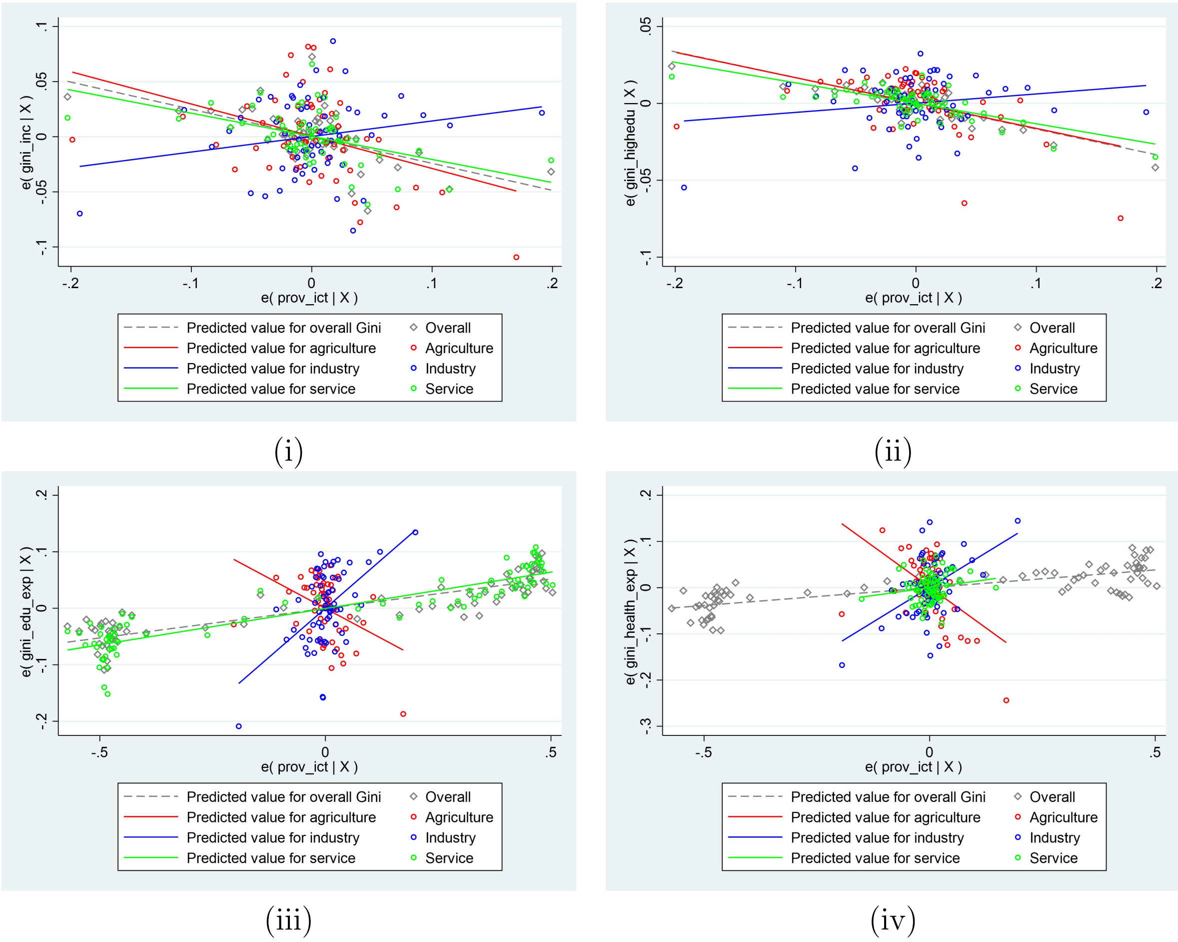
impacts of ICT are related to the labour force's skills in different economic sectors.

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 1.9. 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.

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

Figure 1.9: Association between Gini coefficient and ICT penetration, by economic sector



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 1.6. 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 1.6: 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.

1.5 Conclusions and Policy Implications

Thailand's implementation of ICT policies has many variations from the past to the present. However, it 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.

The DiD and Quantile DiD approaches are used to study the impact of ICT policies on inequality. 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. 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. At the same time, 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 they 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.

The results of this paper suggest 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 1.2). 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.

1.6 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.

Adorno, V., Bernini, C., and Pellegrini, G. (2007) 'The impact of capital subsidies: New estimations under continuous treatment', *Giornale degli economisti e annali di economia*, pp. 67-92.

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. Available at: https://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. Available at: https://doi: 10.1146/annurevpublhealth-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.

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

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. Available at: https://doi: org/10.1007/978-

3-540-25944-2$_{1}$45.

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. Available at: https://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. Available at: https://doi: 10.1093/alcalc/agw050.

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. Available at: https://doi: 10.1177/1363459308090051.

Liu, X. (2010) *Inequality in the Digital World.* All Theses. 766. Available at: https://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). Available at: https://doi.org/10.1186/s12992-018-0385-2.

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. Available at: https://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. Available at: https://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. Available at: https://doi: 10.1111/ajr.12585.

1.7 Appendix

Table A1.1: 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 A1.2: 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 A1.3: 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 A1.4: 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 A1.5: 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 A1.6: 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 A1.7: 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 A1.8: 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 A1.9: 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 A1.10: 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.

Chapter 2

ICT with Time-Varying Adoption, Usage Behaviour and Health Problems

Abstract

This study applies the newly developed difference-in-differences approach to examine the effect of ICT adoption in multiple time periods and to evaluate the impact of ICT usage behaviour on physical and mental health problems throughout the implementation of ICT policies. The dataset in this study, including Health and Welfare Survey (HWS) and ICT Using Survey (ICTH) were assembled by National Statistical Office of Thailand (NSO). ICT adoption at different times begins to affect health at different probabilities in magnitude to cause illness. The ICT adoption cohort would take a long time to affect physical health compared to mental health, which had a relatively early impact and a greater likelihood of illness. As for the ICT usage behaviour, time spent affects muscle inflammation and blood pressure. Some ICT activities, such as learning, result in all health outcomes. Other activities, including social media and entertainment, impact blood pressure and depression. Policymakers should be aware of the negative impacts caused by ICT policies and propose solutions based on user age groups from the heterogeneity of

I wish to thank Professor Marco Francesconi and Dr Xiaoyu Xia for valuable guidance, Associate Professor Akarapong Untong, Dr Natthapon Anantanasan and Dr Theerayuth Phiriyaarayakul for suggestions about data fusion technique and seminar participants at the University of Essex for helpful comments.

impacts.

2.1 Introduction

The information and communication technology (ICT) revolution that drives the exponential advancement of technology coupled with the acceleration of globalization is essential to driving economic growth, leading to the transformation of the way to work, learn, communicate and live (Jorgenson and Vu, 2016). During the 1980s, there was a rapid spread of ICT innovations such as computers (Nuvolari, 2020). Since that, there has been a continuous development toward broadband connectivity and mobile phone coverage until entering the digital technology era, for example, artificial intelligence, the internet of things, big data analytics, social media, blockchain, etc., which is the latest phase of the ICT revolution known as digital transformation (Bodrožić and Adler, 2021). One of the most evident outcomes of the progress of ICT is possibly the internet, which could drastically change economic activities and the social environment.

The benefits of ICT are economic and social progress. This awareness is reflected in numerous initiatives worldwide at all levels, many of which aim to drive positive ICT growth and help its development. ICT is considered to have more significant effects on fulfilling human needs than monetary income because it improves the overall quality of life. However, the ICT revolution also brings many hazards and the effect is only sometimes shown as positive depending on its application in different sectors (Gholami *et al.*, 2010). Therefore, the assessment should link ICT implementation to variables that reflect human development in areas such as standard of living, job creation, education, health, etc. ICT has highly significant positive effects on human development in developing countries. While the high usage of ICT in developed countries possibly has negative consequences on human development concerning ICT impacts on human health (Karaman Aksentijevi´c, Reži´c and Zaninovi´c, 2021). There are some studies in developing countries in both Africa and ASEAN on the impact of ICT on health that indicate the positive relationship between ICT and health outcomes by decreasing mortality rate and increasing life expectancy (Khovanova-Rubicondo, 2011; Dutta, Gupta and Senguptaim, 2019; Mithas, Khuntia, and Agarwal, 2009). Although studies on the impact of ICT on health outcomes in developing countries reveal favourable results, the adverse effects should not be overlooked. This is because ICT is expected to have an even greater impact in the future that could have the same negative impact on health as in developed countries.

As for the impact of ICT policy from the first chapter results, there remains to be scepticism as to whether the rising healthcare expenditures are due to access to accurate healthcare information through ICT use or increased morbidity. To examine such issues, ICT adoption could be one factor affecting people's health due to the intensive use of behaviour through various activities such as working, learning, communication, and social media (Kautiainen *et al.*, 2005; Cassidy-Bushrow *et al.*, 2015). Furthermore, although Thailand's ICT policy has been rolled out nationwide since 2001, only some people have access simultaneously. ICTs are being adopted at different times, which should have different effects. Therefore, this study aims to examine the effect of ICT adoption in multiple time periods. The impact of ICT usage behaviour on physical and mental health problems is investigated throughout the implementation of ICT policies and considered in-depth heterogeneity. Novel econometric techniques are employed to better identify the causal impact, enabling policymakers to plan and formulate measures to cope with potential consequences.

This study is analysed using Health and Welfare Survey (HWS) and ICT Using Survey (ICTH) from NSO covering 1996 to 2019. Preliminary data show a shift in ICT usage behaviour over the past decade, both with increased intensity of use and a focus on ICT use for communications and social media. In analysing the effects of ICT with time-varying adoption, the nonlinear Staggered DID approach was applied to examine the health impact in five diseases: muscle inflammation, blood pressure, vision, stress/migraine/poor sleep and depression.

The first adoption of ICT was the key variable used in this analysis, indicating different effects of timing cohorts. Initially adopting an ICT policy takes time to manifest health effects, which may only become evident after the policy has been in place for some time. The delayed effects of late adoption are likely influenced by evolving usage behaviours. Generally, the physical health impacts of ICT adoption required more time compared to mental health impacts, varying depending on the age group of ICT users.

ICT usage behaviours contributed to the incidence of health problems based on the number of active days, hours per day, and activity patterns. Time spent on ICT statistically significantly affected physical health, including muscle inflammation and blood pressure. At the same time, some activities of ICT use affect physical and mental health, for example, learning, social media, and entertainment. The heterogeneity analysis was performed to identify different effects in time spent on ICT in different activities to obtain more precise solutions. One additional analysis has been used to study the impact of different behaviours on different age groups.

Based on the results, ICT policies tend to have health implications, which policymakers should be more aware of and urgently address. ICT usage behaviour is one of the critical issues that should be considered in policy formulation, taking into account differences between age groups.

The remainder of this study is organised as follows. Section 2 provides the related literature. Section 3 outlines the policy context and related events and introduces the data used in the empirical analysis. Section 4 shows the results of ICT policy on health outcomes from difference-in-differences with multiple time periods estimation by analysing data at the individual levels. It also shows the effect of ICT usage behaviour. The last section ends with the conclusions and policy implications.

2.2 Related Literature

2.2.1 Health and economic development

Since health is a form of human capital and related to labour market success, health impacts labour productivity (Strauss and Thomas, 1998). Some health problems can be so debilitating that they can negatively affect work performance. The workers suffering from certain restrictions caused by health issues are paid lower wages than they would receive (Rodriguez-Alvarez and Rodriguez-Gutierrez, 2018). Regarding this crucial problem, Murphy and Topel (2006) developed an economic framework for valuing social values of increased longevity from healthy. Life extension is also valued in economics because of the increase in goods and leisure utility over a more extended period.

Furthermore, health plays a role in transmitting economic status between generations. That is considered intergenerational transfers and risk in intergenerational mobility processes (Pfeffer and Schoeni, 2014). The parental socioeconomic status affects child health then child health affects their future educational and labour market outcomes. It is more apparent that health problems in children might impede human capital development (Currie, 2009). The results of this literature have significant implications in terms of economic policy. The development of public healthcare affects the country's economy. Suppose the development of public health is better with efficiency, effectiveness, equality and equity. In that case, it will lead to better health for the people, fewer illnesses or mild and non-chronic illnesses. Therefore, the country's economy will improve without the state wasting its budget or unnecessary expenses on health or illness. The fact that most people are in good health can generate productivity or income for themselves and the country.

2.2.2 The impact of ICT on health

Information and communication technology (ICT) has the potential to encourage the sharing of knowledge, efficiency and innovation leading to change in social and human development, including health, education and standard of living (Iqbal, Hassan and Peng, 2019). ICT reforms should be strategically placed to achieve optimal and beneficial utilization. Therefore, the policy aspect considers the impact on people's health outcomes in development (Hamel, 2012).

One piece of evidence from the study by Văidean and Achim (2022) found the relationship between ICT and health outcomes inverted U-shape. They explain that the increased development of ICT drives better healthcare outcomes but does not exceed certain thresholds if, beyond that, ICT provides fewer health benefits, including life expectancy, mortality rate and measles immunisation of children. ICT usage could affect both physical and mental health problems. The relationship between ICT and health is that not only ICT accessibility but also frequency and intensity of use and thus is connected to health behaviours (Leena, Tomi and Arja, 2005). For physical health concerns, physiological issues can result from excessive ICT use. In older age groups, providing new information concerning the implications of intensive ICT use (frequency of internet use) may affect other aspects of daily life by examining the correlation between ICT activity and general activity (Näsi, Räsänen and Sarpila, 2012). In addition, the time spent on ICT is one of the significant factors affecting health. Cassidy-Bushrow *et al.* (2015) reported that heavy internet users were statistically significantly more likely to elevate blood pressure than light internet users. While Kautiainen *et al.* (2005); Lajunen *et al.* (2007); Yen *et al.* (2010), and DiNardi, Guldi and Simon (2019) pointed out the increased times spent on ICT were associated with increased prevalence of overweight and obesity which DiNardi, Guldi and Simon (2019) also indicated that the internet increases weight gain through increased sedentary or dynamic activities.

The office syndrome in office workers caused by long-term work was another physical health issue discussed in the effects of ICT. This disease is a cumulative wound caused by repetitive computer use behaviours, including laptops, desktops, tablets and other display devices, causing severe chronic muscle inflammation (musculoskeletal symptoms: neck pain, back pain and shoulder pain) and also affecting vision from prolonged computer use or namely computer vision syndrome. Illnesses often cause burning sensation, eyestrain, eye fatigue, dry eye and unclear images (Blehm *et al.*, 2005; Somcharoen and Dickie, 2019; Anggrainy, Lubis and Ashar, 2020). Dessie *et al.* (2018) pointed out that most computer users are suffered from computer vision syndrome. Apart from the health problems, the illness causes inefficiency in the workplace and deteriorates the quality of work. The main risk factors for developing the disease were female gender, years of computer use, more than four hours of daily computer use, and eye discomfort during computer use (Ekşioğlu, 2017).

A study by WHO (Sánchez, 2006) about mobile phone use on cancer risk found no evidence to support this association due to the short-term data. Therefore, the risks of long-term effects cannot be explained. There is strong evidence that the dangers of using mobile phones while driving pose a significant risk of accidents. However, recent studies by Shih *et al.* (2020) and Choi *et al.* (2020) argued that overuse of smartphones significantly increases the risk of cancer, especially among those addicted to smartphones and behaviour of smartphone use before bedtime.

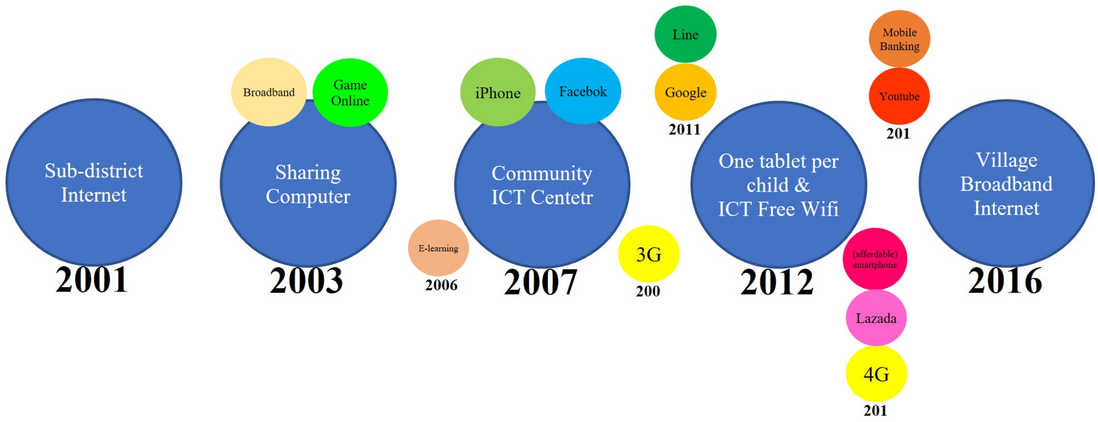
In part of mental health implications of ICT usage, some studies have reported that ICT use results in symptoms of depression, anxiety, social isolation and self-harm. Due to concerns about the widespread use of ICT devices before bedtime, a causal effect study identifies that internet access can disrupt sleep by reducing sleep duration and satisfaction and then negatively affecting health and cognitive performance (Billari, Giuntella and Stella, 2018). In addition, the effects of smartphone use on increasing the duration and frequency of headaches in migraine patients were examined by Demir and Sümer (2019). Excessive smartphone use in migraine patients is associated with poor sleep quality and daytime sleepiness, reducing the quality of life. A longitudinal study showing high levels of internet use was a risk factor for future mental health problems by examining the impact of gender differences (Mars *et al.*, 2020; Shin *et al.*,2022). However, it may depend on the purpose of using the internet. Using the internet to communicate with family and friends can help reduce depression, but using the internet too often can be harmful (Bessière *et al.*, 2010). Internet access has a statistically significant effect on mental health, particularly in young cohorts, and there are similar results for hospitalizations and self-harm (Donati *et al.*, 2022). This is consistent with the study by Braghieri, Levy and Makarin (2022) that social media is likely to increase the deterioration in mental health among adolescents and young adults. In addition, accessing certain information via the internet could have a significant detrimental effect on mental health. For example, news about suicide methods from internet channels influences suicidal thoughts (Sueki, 2013). However, in some studies of the effects on mental health among older adults from internet use, a positive contribution was found since the internet promoted interpersonal interactions, increased access to community resources and empowered them at the social level (Forsman and Nordmyr, 2017). Therefore, internet use may help encourage older adults to decrease isolation and depression (Cotten *et al.*, 2014).

In summary, ICT significantly enhances quality of life, yet improper use can potentially impact both physical and mental health, thereby hindering overall development. Thailand has continuously invested in ICT, but it has yet to be proven how ICT policies benefit or harm the Thai people or the country, especially regarding health. Hence, it is essential to study this to gain a thorough understanding leading to effective ICT policy formulation that benefits those who access it, emphasising the need for appropriate use, which emphasises significant policy implications.

2.3 Background and Empirical Strategy

Throughout the implementation of the ICT policy in Thailand since 2001, the Thai government has determined to use ICT to enhance people's quality of life by investing in ICT infrastructure and promoting accessibility through various policies continuously, as shown in the big dark blue circles in Figure 2.1. During that period, many ICT-related events cause public response, such as high-speed wireless networks, smartphones (especially at an affordable price from China), search engines and many social media applications.

Figure 2.1: ICT policies and ICT-related events



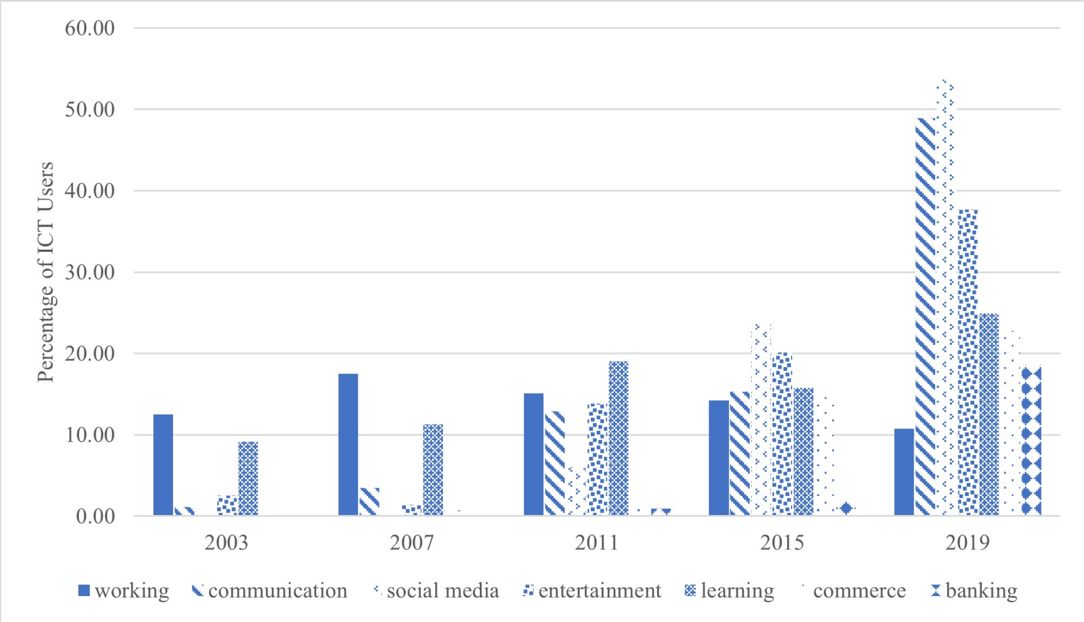
These policies and government support have resulted in most Thai people adopting ICT as part of their daily lives through various activities that influence both work and leisure. According to a survey by the National Statistical Office of Thailand (2021), the proportion of ICT users in various activities over the past decade has seen a significant pattern change, likely based on the development of ICT applications and the response to users' needs. Figure 2.2 illustrates a relatively high growth proportion in some ICT activities, including communication, social media, e-commerce and Internet banking. However, it can be seen that activities related to working tend to decline.

In addition, ICT users are likely to change their daily habits of ICT use due to the frequency of use and time spent on ICT (Näsi, Räsänen and Sarpila, 2012). Over the past 15 years, Thai people tend to spend more time on ICT, with a noticeable decrease in hours of use for 1-2 hours per day. While the usage of more than 2 hours is increasing, as shown in Figure 2.3.

2.3.1 Data

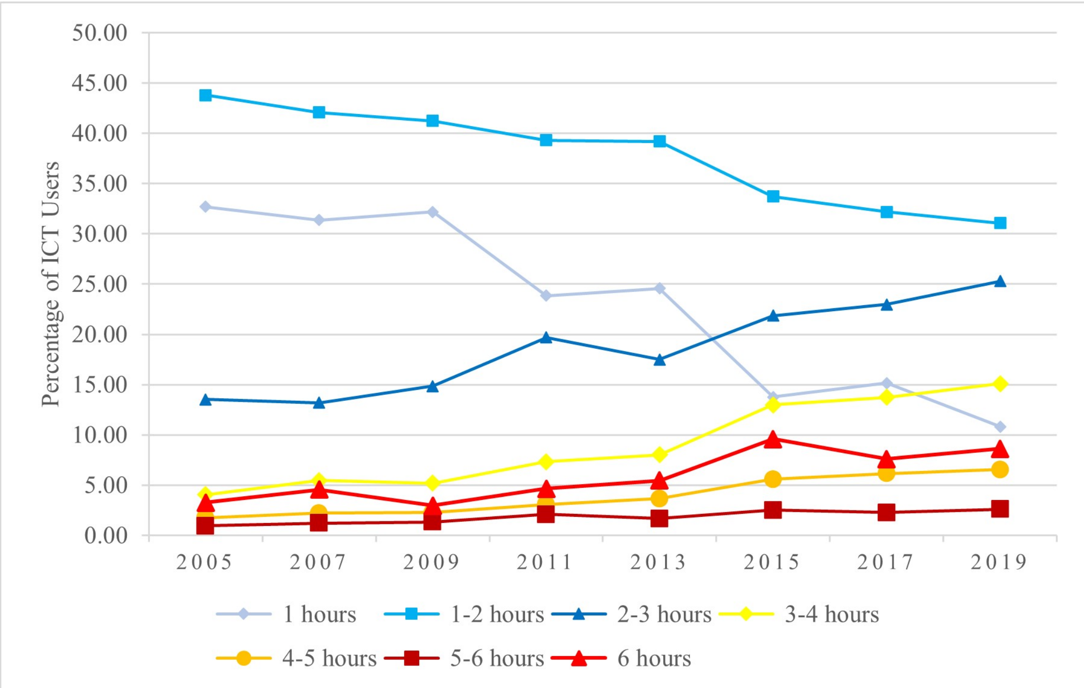
This study relies on various data sources from Thailand's National Statistics Office (NSO). The data sets are Health and Welfare Survey (HWS) and ICT Using Survey (ICTH). HWS contains data on individual health issues and sociodemographic characteristics, which are

Figure 2.2: Changing the activity of ICT use



Source: National Statistical Office of Thailand (2021).

Figure 2.3: Changes in time spent on ICT among users



Source: National Statistical Office of Thailand (2021).

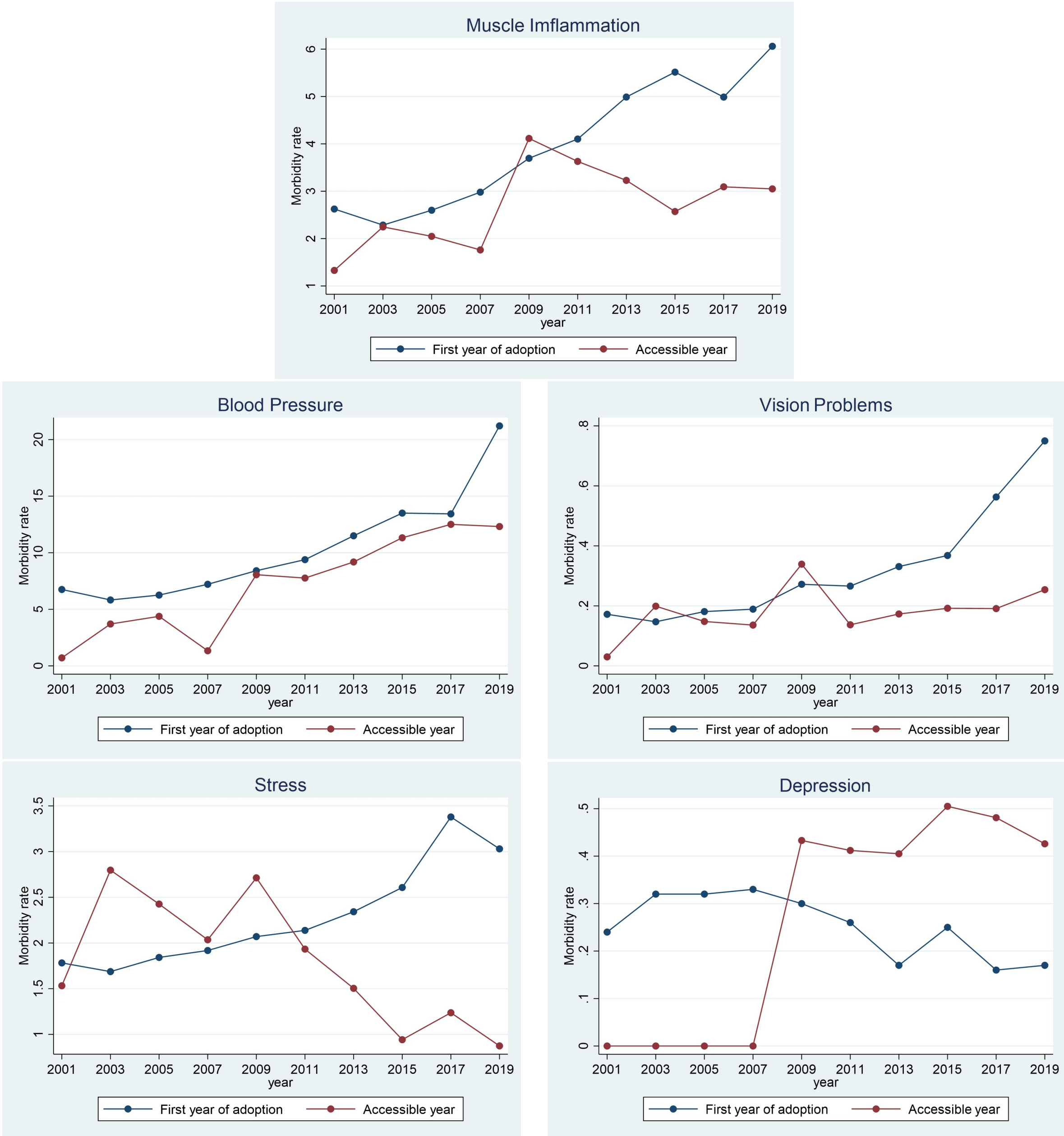
surveyed every two years. ICTH provides household and individual data on the ICT usage behaviour of individuals and the use of ICT devices in households and sociodemographic characteristics, which have been surveyed annually since 2001. This research will harmonize different surveys and combine these data with the data fusion technique to extend the analysis into the panel data (Saporta, 2002; Aluja-Banet *et al.*, 2015; D'Orazio, 2016). Data include primarily NSO public opinion polls, going back to 1996 and has over 39,000 individuals in each year from 11 years. In total, about 400,000 observations are used in the study. In addition, the sample age has been selected from 13-88 years old to divide the analysis cohorts according to the age range (youth, adults and elders). Variable definitions and descriptive statistics on all variables used are displayed in Appendix Table A2.1.

Based on many studies on the effect of ICT use leading to illness, the potential outcomes employed in this empirical strategy are probable diseases that can be categorized as physical and mental. Considering physical health, muscle inflammation and vision problems are illness variables that indicate office syndrome from ICT usage (Blehm *et al.*, 2005; Dessie *et al.*, 2018; Somcharoen and Dickie, 2019; Anggrainy, Lubis and Ashar, 2020). Another possible variable is high blood pressure (Cassidy-Bushrow *et al.*, 2015), resulting from too much time on ICT. Regarding mental health outcomes, Bessière *et al.* (2010), Mars *et al.* (2020), and Shin *et al.* (2022) considered depression as a critical variable. While Billari, Giuntella and Stella (2018), Demir and Sümer (2019) and Thomée, Härenstam and Hagberg (2012) used some symptoms that are influenced by the mental state, including stress, migraine and poor sleep.

The vital variable used in the analysis to be the treatment variable is the first year of ICT adoption (the blue line), as shown in Figure 2.4, which be considered a group or cohort in the analysis. It is different from the classification of ICT access groups following the accessible year that identifies only binary treatment indicators which provides calendar time results. Figure 2.4 compares morbidity rates of 5 diseases possibly related to ICT use between the first year of ICT adoption and the accessible year.

The bar charts in Figure 2.5 illustrate preliminary evidence for an association between ICT adoption and illness. It indicates the fraction of individuals who have health problems compared between the cohort of first-year adoption in ICT and not-yet ICT

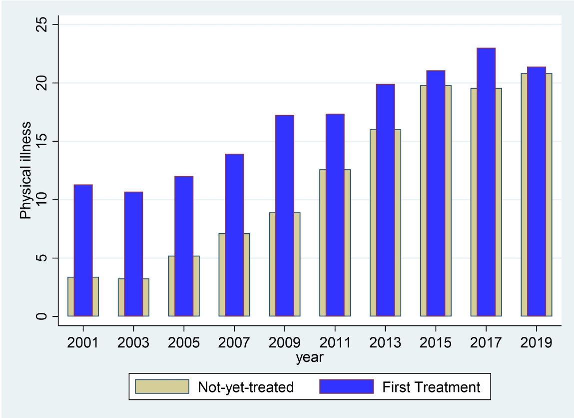
Figure 2.4: Illness rate comparison with the first year of ICT adoption and accessible year, 2001-2019

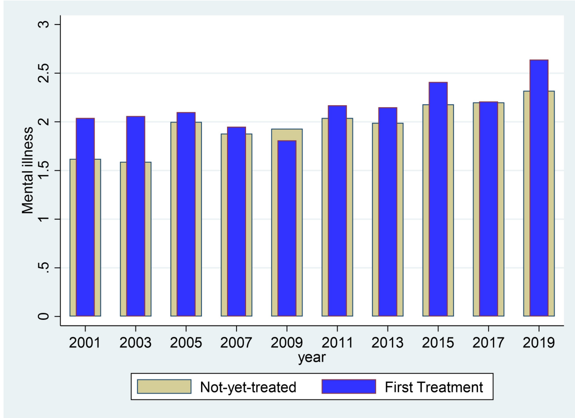


adoption. Overall, physical and mental illness tend to increase through the first-year adoption of ICT, obviously in physical ones.

In this dataset, when categorising the use of ICT by age groups, which are youth (15-24 years), adults (25-59 years) and elders (60 years and older), there is a proportion of adopting ICT for the initial time, as shown in Figure 2.6. At the initiation of the policy, the first five years of ICT adoption were more than 50%. It seems that at the beginning of

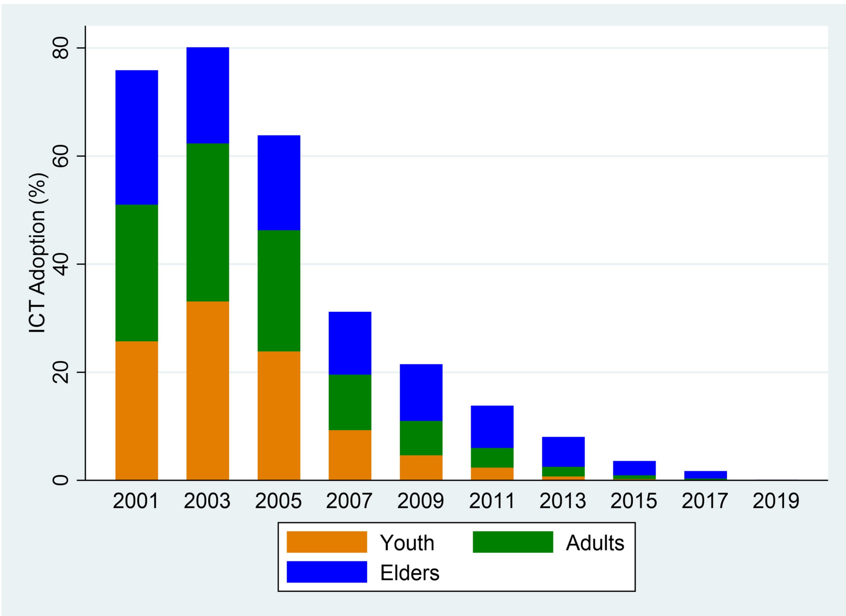
Figure 2.5: Illness rates and ICT adoption, 2001-2019





the policy and the first adoption of ICT, youth and adults had a more significant proportion of ICT adoption than the elders. However, the proportion of the elders who adopted ICT for the first time continued in the following years.

Figure 2.6: The ICT adoption rate, by age group



2.3.2 Research Methods

The one hypothesis in this study is that ICT adoption at different times could have different effects on health. In particular, some issues probably take longer for the impacts to appear. Goodman-Bacon (2021) pointed out variations across groups of individuals or units that obtain treatment at different periods. This differs from the traditional difference-in-differences (DiD) method, considering analysis from only two groups and two time periods. Multiple individuals adopt the treatment, but they adopt it at different times. Therefore, this is unclear “pre” and “post” treatment. This type of relative grouping is not only treated and not treated but also early and late treated. In newly developed DiD, the units are split into different timing cohorts based on when the first treatment takes place and can use not-yet-treated units as a comparison group (Callaway and Sant’anna, 2021).

The ICT technology policy has been implemented since 2001. However, Thai people have ICT accessible at different times. This study exploits more policy variation than was available in the previous chapter. The strategy can be applied broadly within the framework to evaluate the impact of technology policy on potential outcomes, allowing estimation of the following Difference-in-Differences (DD) model for all outcome variables included in the main baseline specification:

$$Health_{it} = \alpha + \beta_i + \gamma_t + \delta Firsttreat_{it} + \omega X'_{it} + \varepsilon_{it} \tag{2.1}$$

where $Health_{it}$ is the outcome of individual i at time t, β_i is an individual fixed effect, γ_t is a year fixed effect, $Firsttreat_{it}$ is the treatment indicator X'_{it} a vector of control variables, and ε_{it} is a residual disturbance. $Firsttreat_{it}$=1{t−G$_i$≥ 0}, where G_i indicates the period individual i at time t is first treated (cohort) or policy adoption year. The coefficient of interest is δ, which captures treatment effect heterogeneity over time.

The outcome denoted $Health_{it}$, is a dummy variable equal to 1 if individual i has chronic health problems within 1 year before the interview at time t and 0 if the individual i has no chronic health problems. However, the dependent variables from equation (2.1) are not continuous variables. If the dependent variable is a dummy variable, it is called a “binary choice model”, then it cannot be analysed by simple linear regression. Therefore, this study employs Probit/Logit regression model for estimation. The nonlinear Staggered DID approach could be considered the Logit model proposed by Wooldridge (2022).

Another hypothesis in this study is that ICT usage behaviour has an impact on health, whether it is physical health or mental health. The analysis can be divided into two parts. First, the frequency of ICT use tends to affect health. Noticeably, the treatment variable in the model is multi-valued or continuous to figure out treatment effects at different doses. Hence, this study applies the difference in differences with a continuous treatment using a TWFE regression (Acemoglu, Autor and Lyle, 2004; Callaway, Goodman-Bacon and Sant'Anna, 2021). This strategy can be generalized to the framework to estimate the following model for all outcome variables.

$$Health_{it} = \alpha + \beta_i + \gamma_t + \theta ICTusage_{it} + \omega X'_{it} + \varepsilon_{it} \tag{2.2}$$

where $Health_{it}$ is the outcome of individual i at time t, β_i is an individual fixed effect, γ_t is a year fixed effect, $ICTusage_{it}$ is the time spent on ICT of individual i at time t, X'_{it} a vector of control variables, and ε_{it} is a residual disturbance. The coefficient of interest is θ, which captures treatment effect heterogeneity over time.

Since the outcomes are binary variables, the DiD approach could be considered the linear probability model or Probit/Logit model proposed by Ai and Norton (2003). These non-linear methods can identify the incremental effect of the DiD coefficient (Puhani, 2012). The explanatory variable indicates ICT usage behaviour, including the number of days of ICT use per month and hours of ICT use per day.

Second, this study aims to develop evidence on the health problems effect of ICT usage behaviour. The explanatory variables that indicate ICT activities and reflect ICT usage behaviour consist of work, communication (video call, chat), social media, entertainment (watching movies, listening to music, playing games), learning (study, e-learning, e-book, search engine), e-commerce and internet banking. The effect of ICT activities on health problems is estimated using a logit model.

$$\begin{aligned} Health_{it} &= \alpha + \beta_i + \gamma_t + \tau_1 work_{it} + \tau_2 commu_{it} + \tau_3 soc_{it} \\ &+ \tau_4 ent_{it} + \tau_5 learn_{it} + \tau_6 commerce_{it} + \tau_7 bank_{it} + \omega X'_{it} + \varepsilon_{it} \end{aligned} \tag{2.3}$$

where $Health_{it}$ is the outcome of individual i at time t, β_i is an individual fixed effect, γ_t is a year fixed effect, $work_{it}$, $commu_{it}$, soc_{it}, ent_{it}, $learn_{it}$, $commerce_{it}$, $bank_{it}$, is ICT activities of individual i at time t, X'_{it} a vector of control variables, and ε_{it} is a residual disturbance. The coefficient of interest is τ. Each explanatory variable is dummy variable equal to 1 if individual i has such activities within 1 year before the interview at time t and 0 if the individual i has no activities.

All specifications include the controls for individual demographics and characteristics: gender, age, smoking and alcohol consumption.

2.4 Empirical Findings

2.4.1 ICT with time-varying adoption

This study initially estimates coefficients by employing nonlinear DiD with multiple time periods and providing results using the not-yet-treated individuals as the comparison group. The results in Appendix Table A2.2 are based on equations (2.1), illustrating the effect of ICT adoption on physical health with individual and year fixed effects. Such results are displayed as contrasts of predictive margins value and the different aggregated treatment effect measures, including cohort, event study and calendar time.

Considering the simple margin, ICT adoption does not affect physical health overall. However, when examining the cohort-specific effects of the first-year ICT adoption, there is an impact probability on the cohorts in 2001, 2005 and 2007. When comparing the calendar time effects, no health effects were found except in 2015. The dynamic treatment effect can interpret from an event study, which shows the treatment effects by the length of exposure to the ICT adoption. So, the impact of ICT adoption on physical health and the most significant magnitude was found in the longest event.

The cohort-time marginal treatment effects results are depicted in Figure 2.7 to clearly show how the marginal values influenced outcomes in any direction and differ from 0 with statistical significance. In addition, the impact between each first adoption cohort can be compared with base-level coefficients.

The cohort-time marginal treatment effects found that initiating ICT adoption at different times affects physical health at different times and has different probabilities in magnitude to cause illness. It seems that in some cohorts, for example, those who have adopted ICT since 2001, it will take a long time to affect their physical health and those who have just started adopting ICT in 2015, have not been affected.

As for the impact on mental health in Appendix Table A2.3, results have differed from physical health because ICT adoption was found to have a probabilistic effect on mental health, even at a simple margin value. Additionally, all the cohorts adopting ICT had a probability of developing mental health problems, with the highest probability size being in the 2007 cohort. The summary parameters aggregated by cohort-specific and calendar time effects were relatively consistent. The event study begins to affect at e=2, and the greatest magnitude was found in the longest event.

Figure 2.7: ICT adoption cohort-time marginal treatment effects on physical health

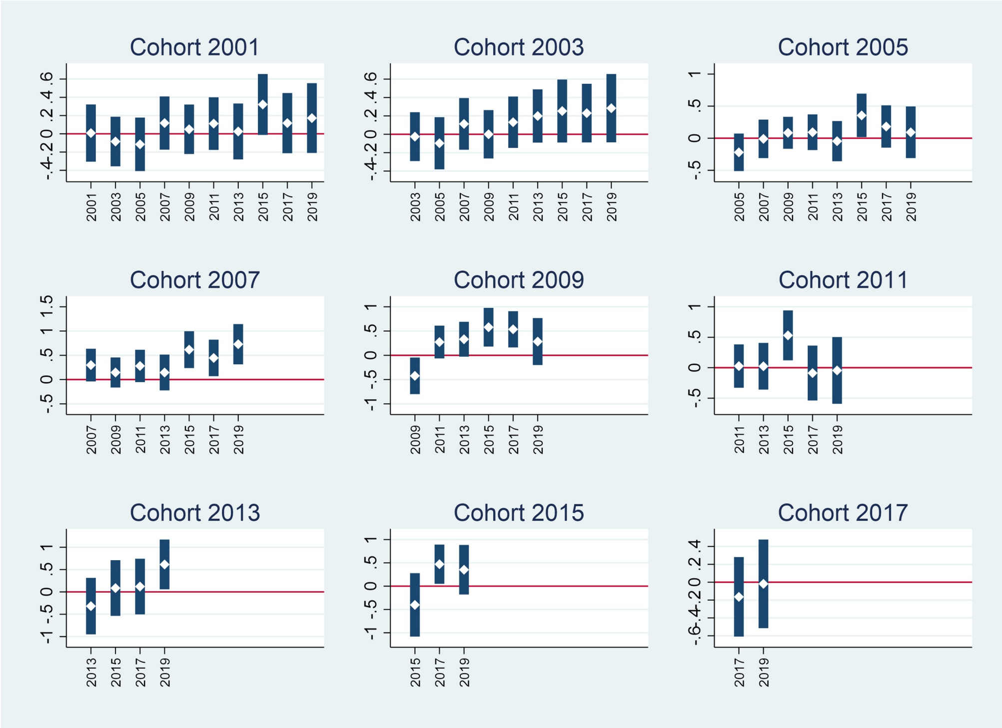
Figure 2.8 shows the cohort-time marginal treatment effects on mental health. It seems that each cohort who first adopted ICT at different times had a relatively early impact on mental health and a greater likelihood of illness than physical health.

Heterogeneity analysis

To study the health effects of ICT adoption, one heterogeneity that should be considered further is by the age group since the ability to adopt ICT at different times of each age group, as shown in Figure 2.9, is likely to have different health implications. Appendix Table A2.3 provides the aggregate results.

There were different health impact patterns between age groups. When they first adopted ICT, it took a relatively long time for youth to experience health effects in the early stages of the policy. However, ICT adoption by youth since 2007 has been affected faster. Adults are affected relatively early on health after the first adoption of ICT, possi-

Figure 2.8: ICT adoption cohort-time marginal treatment effects on mental health



bly due to working age, especially among those who first adopted ICT in 2005, 2007 and 2013. All cohorts of older people who adopt ICT have different effects on their health but at different times. At the beginning of the ICT policy, it took longer for elders to experience health effects from adopting ICT. Until adopted in 2005, the health effects were faster.

2.4.2 ICT usage behaviour

Table 2.1 displays estimating equation (2.2) results with ICT usage frequency. ICT usage behaviour studies on health problems based on the number of active days per month and the number of hours spent per day on ICT. When considering each disease, ICT usage frequency appears to have a statistically significant impact on muscle inflammation and blood pressure—furthermore, the effect of frequency of ICT usage on depression but not significant effect. The estimated coefficients on each health outcome, as illustrated in Figure 2.10, show that the frequency of ICT use affects health in some illnesses, both the number of days spent per month and the number of hours spent per day.

Table 2.1: Effect of ICT usage frequency on health

	Physical illness			**Mental illness**	
	Muscle inflammation	Blood pressure	Vision problem	Stress/Migraine/ Poor sleep	Depression
Days	0.002*				
	(0.001)				
		0.001**			
		(0.001)			
			-0.010*		
			(0.005)		
				-0.003*	
				(0.002)	
					-0.002
					(0.003)
Hours	0.001				
	(0.006)				
		0.005*			
		(0.004)			
			-0.064***		
			(0.025)		
				-0.013**	
				(0.006)	
					0.012
					(0.013)
Controls	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	110,924	200,598	8,624	79,739	11,242

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.

Another study of ICT usage behaviour as ICT activities on health problems based on equation (2.3), the results of the analysis revealed in Table 2.2. Seemingly, the use of ICT for learning has a statistically significant effect on health in all diseases. While social media and entertainment affect blood pressure and depression. Figure 2.11 clearly shows the estimated coefficients affecting health issues. It seems that ICT activities that affect health have a stronger effect on mental illness than physical ones.

Table 2.2: Effect of ICT activities on health

	Physical illness			**Mental illness**	
	Muscle inflammation	Blood pressure	Vision problem	Stress/Migraine/ Poor sleep	Depression
Working	0.045	-0.046	-0.047	0.026	-0.005
	(0.043)	(0.030)	(0.181)	(0.047)	(0.104)
Communication	-0.051	-0.060*	0.001	-0.071	-0.126
	(0.057)	(0.037)	(0.249)	(0.069)	(0.125)
Social media	-0.135**	0.175***	-0.415	-0.521***	0.500***
	(0.060)	(0.038)	(0.260)	(0.075)	(0.134)
Entertainment	0.052	0.116***	-0.424*	0.066	0.362***
	(0.054)	(0.035)	(0.245)	(0.064)	(0.124)
Learning	0.094**	0.086***	0.327*	0.123**	0.264**
	(0.049)	(0.033)	(0.205)	(0.056)	(0.112)
Commerce	-0.102*	-0.028	-0.087	-0.222***	0.047
	(0.063)	(0.039)	(0.289)	(0.085)	(0.124)
Banking	0.025	-0.073	0.230	-0.370***	-0.112
	(0.084)	(0.050)	(0.350)	(0.129)	(0.155)
Controls	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	110,924	200,596	8,624	79,739	11,242

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

Further analyses were conducted to address whether the time spent in different ICT use activities affects health to gain a deeper understanding of the impact of ICT use behaviour on different health, as reported in Table 2.3.

Monthly frequent use of ICT for social media activities may affect muscle inflammation and blood pressure, and when used for entertainment, it can also affect blood pressure. Long-term daily use of ICT for communication, social media and entertainment could cause high blood pressure. In addition, prolonged daily use of ICT for learning tends to increase the incidence of depression. The results of this part underline the surveillance of long-term ICT use in some activities that possibly have a statistically significant effect on health.

Another issue that is worth to be further investigated in studying the impact of ICT use on health is age-group differences, as illustrated in Figure 2.12. Different age groups tend to have different ICT usage behaviour and have different health effects. Among youth, continuous use of ICT for many days may affect physical health, while spending several hours a day tends to affect mental health, especially depression. As for adults, long daily habits could affect both physical and mental health, including blood pressure and depression. For older people, continuous use of ICT for many days and hours a day might have a specific effect on physical health, especially vision.

ICT use among young people affects blood pressure and may cause depression when using ICT for work. The use of ICT for communication probably affects vision problems. In addition, when they use ICT for learning, they may be prone to stress and depression. In adults, ICT use for social media and entertainment seems to cause blood pressure issues and depression. At the same time, ICT use for learning may have adverse health trends in many diseases, including muscle inflammation, blood pressure, stress and depression. ICT use behaviours of older people that affect health are quite different from those of other

Table 2.3: Effect of ICT usage frequency on health in different activities

	Physical illness			**Mental illness**	
	Muscle inflammation	Blood pressure	Vision problem	Stress/Migraine/ Poor sleep	Depression
Days					
×Working	0.002	0.001	-0.005	-0.004***	0.003
	(0.001)	(0.001)	(0.007)	(0.002)	(0.003)
×Communication	0.002	0.001	-0.008	-0.003	-0.0008
	(0.001)	(0.0008)	(0.006)	(0.001)	(0.003)
×Social media	0.003**	0.002**	-0.013**	-0.003	0.0005
	(0.001)	(0.001)	(0.006)	(0.002)	(0.003)
×Entertainment	0.002	0.001**	-0.012*	-0.004	-0.0004
	(0.001)	(0.0008)	(0.006)	(0.002)	(0.003)
×Learning	0.0008	0.0008	-0.004	-0.004**	0.004
	(0.001)	(0.0009)	(0.006)	(0.002)	(0.003)
×Commerce	0.0007	0.0003	-0.007	-0.005**	0.002
	(0.002)	(0.001)	(0.008)	(0.002)	(0.003)
×Banking	0.004	0.0009	-0.004	-0.008**	-0.0001
	(0.003)	(0.002)	(0.010)	(0.004)	(0.005)
Hours					
×Working	0.002	0.003	-0.022	-0.014**	0.021
	(0.006)	(0.004)	(0.027)	(0.007)	(0.013)
×Communication	0.003	0.009**	-0.052*	-0.012	0.008
	(0.007)	(0.004)	(0.030)	(0.008)	(0.013)
×Social media	0.009	0.011***	-0.11***	-0.02**	0.019
	(0.007)	(0.004)	(0.032)	(0.009)	(0.014)
×Entertainment	0.004	0.008*	-0.089***	-0.009	0.014
	(0.006)	(0.004)	(0.033)	(0.008)	(0.013)
×Learning	-0.002	0.003	-0.028	-0.017**	0.023*
	(0.006)	(0.004)	(0.027)	(0.007)	(0.013)
×Commerce	0.005	0.005	-0.05	-0.036**	0.016
	(0.008)	(0.005)	(0.037)	(0.011)	(0.015)
×Banking	0.012	0.007	0.063	-0.029	0.002
	(0.013)	(0.008)	(0.058)	(0.019)	(0.023)
Controls	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	110,924	200,596	8,624	79,739	11,242

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.

groups. Stress/migraine/poor sleep may be caused by using ICT for banking. Lancaster University (2018) has pointed out that many older people tend to be uncomfortable with new technologies. Fear of making mistakes is one reason why older people have anxiety about using them, particularly mobile banking experiences linked to trust (Rajaobelina *et al.*, 2021). (See more details in Appendix Table A2.5 and A2.6)

2.5 Conclusions and Policy Implications

According to the study in the previous chapter, ICT policies resulted in increased healthcare expenditure. That could be because ICT access causes health problems. The cause may be the behaviour of ICT use, both the intensity of use and the activity patterns. This study aims to evaluate the effect of ICT adoption in multiple time periods and to investigate and quantify the impact of ICT usage behaviour on physical and mental health problems throughout the implementation of ICT policies. The newly developed difference-in-differences approach is applied to examine the intervention by using Health and Welfare Survey (HWS) and ICT Using Survey (ICTH) assembled by National Statistical Office of Thailand (NSO).

Over the past decade, ICT users have changed their behavioural patterns with a growing proportion of communication and social media usage. In addition, they have a trend of increasing usage time spent. The newly developed difference-in-differences approach is applied to examine the intervention. The key variable used in the analysis as a treatment variable was the first year of ICT adoption, considered a cohort in the analysis. Unlike classifying ICT access groups by specific access years, only binary treatment indicators yield results based on calendar time.

The empirical result of ICT effect on health problems with time-varying adoption reports the cohort-time marginal treatment effects. It found that initiating ICT adoption at different times begins to affect physical health at different times and has different probabilities in magnitude to cause illness. In addition, the ICT adoption cohort would take a long time to affect their physical health. Meanwhile, each cohort that first adopted ICT at different times had a relatively early impact on mental health and a greater likelihood of illness than physical health. Further studies into health impacts should consider analysing age stratification, which is likely to produce different outcomes. The youth and senile groups who adopted ICT at the early stages of the policy are relatively slower in health impacts. In contrast, adult people would have faster effects. However, between 2005 and 2007, all groups adopting ICT such years experienced faster health effects.

As for the behaviour usage on ICT that affects health, the results provide evidence of a significant impact of ICT usage frequency on muscle inflammation and blood pressure. At the same time, some ICT activities affect both physical and mental health, including learning. It also seems that social media and entertainment tend to impact blood pressure and depression. In addition, further study of how the frequency of ICT use for different ICT activities has different effects on health. The findings of this section highlight the impact of the high duration of certain ICT activities on health problems, including social media, entertainment and communication. The last point analysed the results that may differ between age groups because each age group would likely have different ICT usage behaviours. The younger age group suffers from physical health problems when using ICT continuously for several days and mental health problems when used for long hours. ICT activities for this group that negatively affect health include work, learning and communication. Adults who continue to use ICT high duration are affected by both physical and mental health from social media, entertainment and learning activities. The elder age group could affect vision if high-frequency ICT use is continued for a long time, while stress/migraine/poor sleep might be caused by using ICT for banking.

According to the study results in this paper, Thai people are more likely to have health problems due to the use of ICT, which the new DID approach fulfils dynamic results, thus providing a clearer view of policy impacts. When studying the effects of ICT adoption at varying times, it can be seen that the impact on mental health occurs faster than physical health. This result provides new information beyond the review of relevant literature. Therefore, policymakers should be aware of the prevalence of mental health problems that may highly increase in the future. In addition, some activities that clearly impact health, such as social media (Braghieri, Levy and Makarin, 2022; Shin *et al.*, 2022), coincide with the emergence of smartphones and popular applications such as Facebook (2007). It seems to be a catalyst for the onset of health problems. According to trends in ICT use (Figures 2.2 and 2.3), both frequency of use and activity patterns may increase adverse health effects consistent with Leena, Tomi and Arja (2005) and Cassidy-Bushrow *et al.* (2015). Therefore, in setting policies or proposing solutions, policymakers should also consider the impacts of ICT policies on health because the health problems amongst Thai people would imply an increase in the country's public health budget. In addition, policymakers should consider the different health impacts of each age group that should be detailed in specific groups so that policies can be formulated to cover the issues and stimulate people's acceptance of policies in each group.

Although promoting ICT access by focusing on the development and distribution of infrastructure for more than 20 years has been helpful in driving a country to prosper, technology can have negative effects. Therefore, in addition to the impact on health, there should be additional investigations on the impact of ICT policy on other issues to be useful for comprehensive ICT policy formulation.

Figure 2.9: ICT adoption cohort-time marginal treatment effects on health in different age groups

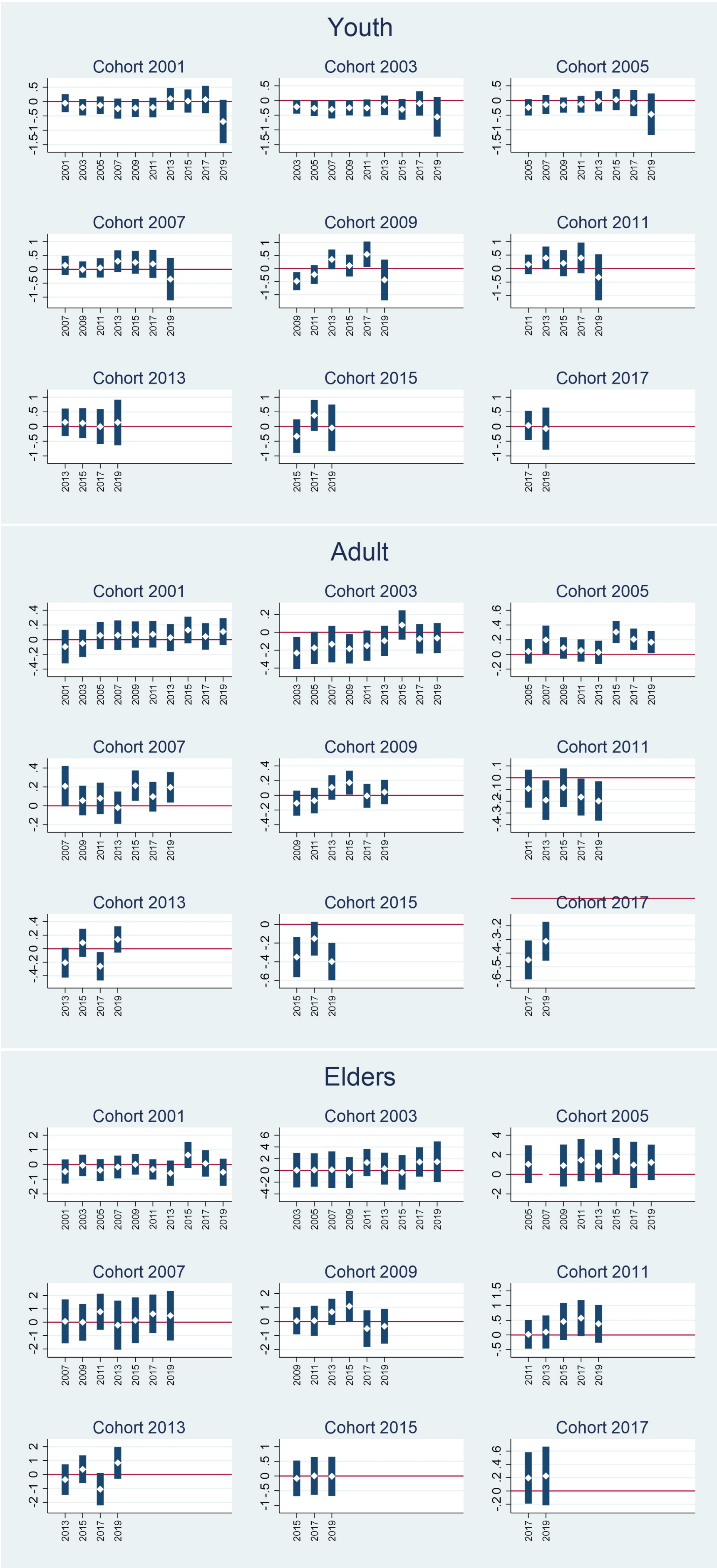


Figure 2.10: Estimated coefficients of ICT usage frequency on each health outcome

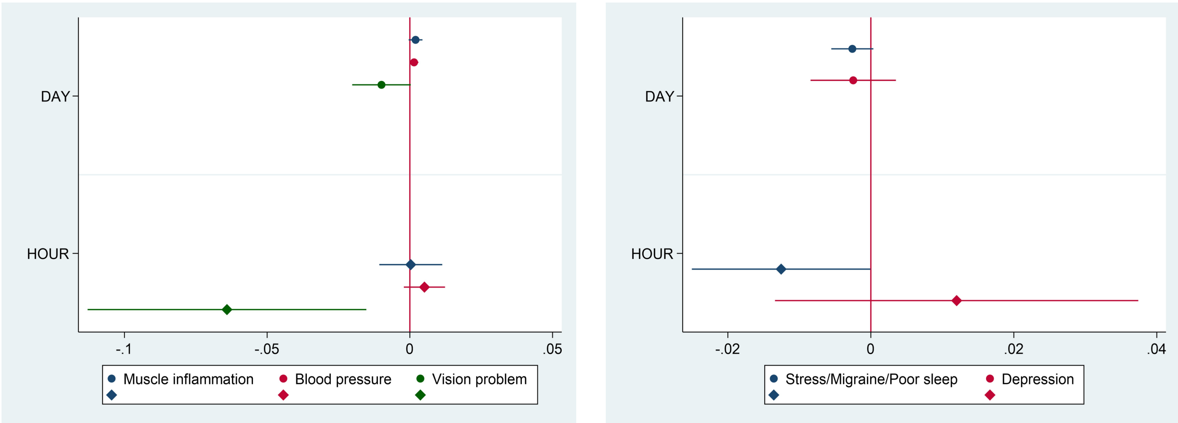


Figure 2.11: Estimated coefficients of ICT usage activities on each health outcome

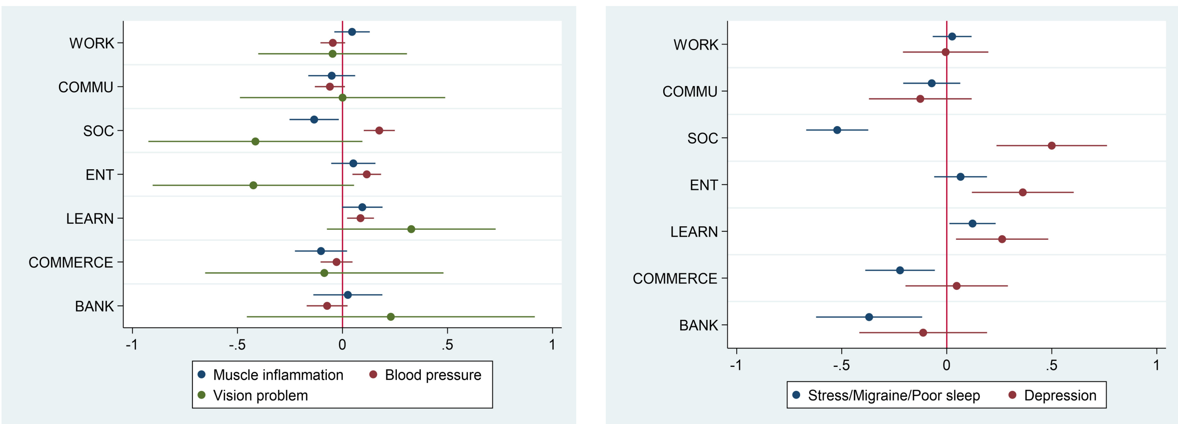
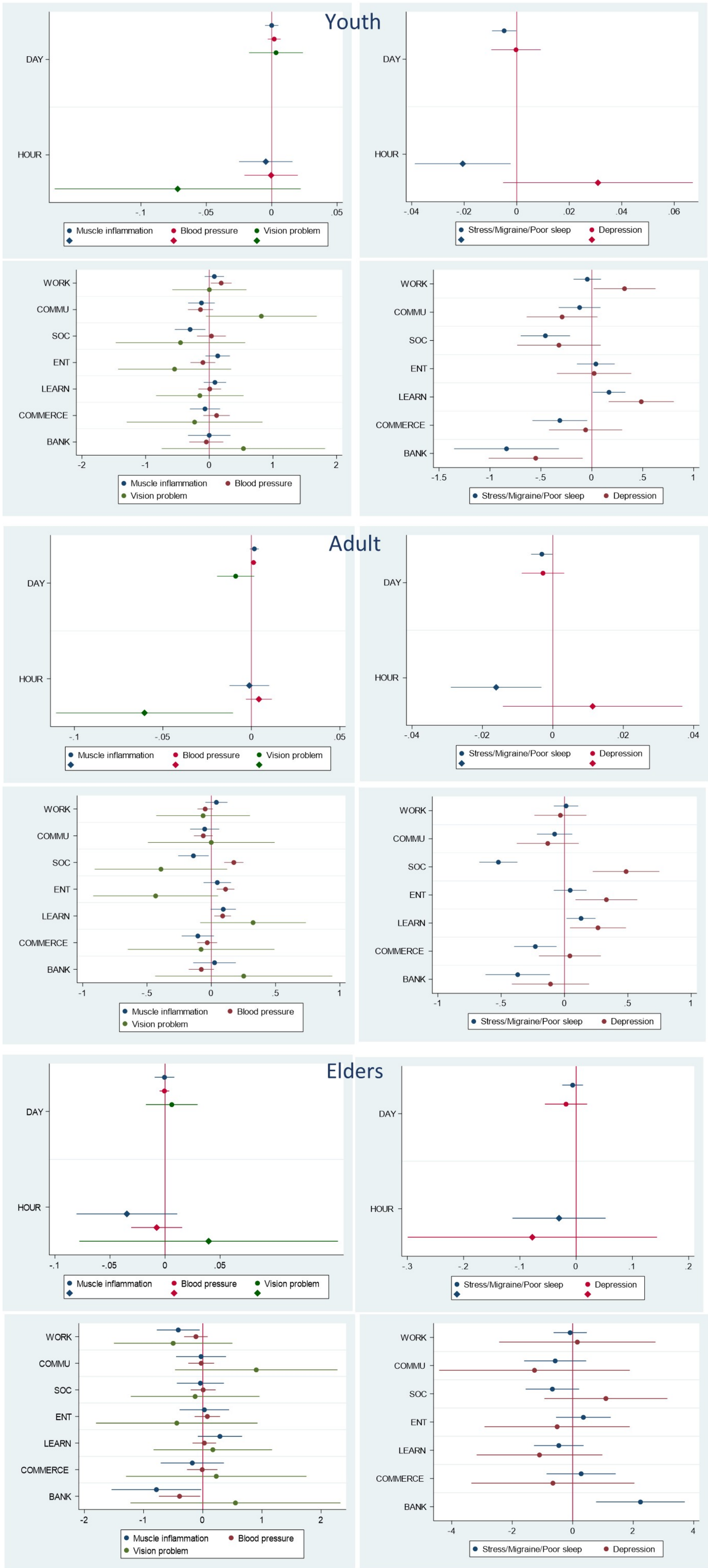


Figure 2.12: Estimated coefficients of ICT usage behaviours on each health outcome in different age groups



2.6 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.

Ai, C. and Norton, E.C. (2003) 'Interaction terms in logit and probit models', *Economics letters*, 80(1), pp. 123-129.

Aluja-Banet, T. *et al.* (2015) 'Improving prevalence estimation through data fusion: methods and validation', *BMC Medical Informatics and Decision Making*, 15(1), pp. 1-10.

Anggrainy, P., Lubis, R.R. and Ashar, T. (2020) 'The effect of trick intervention 20-20-20 on computer vision syndrome incidence in computer workers', *Journal of Ophthalmology (Ukraine)*, 1, pp. 22-27.

Bessière, K. *et al.* (2010) 'Effects of internet use on health and depression: a longitudinal study', *Journal of medical Internet research*, 12(1), pp. e6.

Billari, F.C., Giuntella, O. and Stella, L. (2018) 'Broadband internet, digital temptations, and sleep', *Journal of Economic Behavior and Organization*, 153, pp. 58-76.

Blehm, C. *et al.* (2005) 'Computer vision syndrome: a review', *Survey of ophthalmology*, 50(3), pp. 253-262.

Bodrožić, Z. and Adler, P. S. (2021) 'Alternative futures for the digital transformation: A macro-level Schumpeterian perspective', *Organization Science.* Available at: https://doi.org/10.1287/orsc.2021.1558.

Braghieri, L., Levy, R. and Makarin, A. (2022) 'Social Media and Mental Health', *American Economic Review*, 112(11), pp. 3660-93.

Callaway, B.; Goodman-Bacon, A. and Sant'Anna, P.H.C. (2021) 'Difference-in-Differences with a continuous treatment', *arXiv.* Available at: https://doi.org/10.48550/arXiv.2107.02637.

Callaway, B., and Sant'Anna, P.H.C. (2021) 'Difference-in-differences with multiple time periods', *Journal of Econometrics*, 225(2), pp. 200-230.

Camilleri, S. and Diebold, J. (2019) 'Hospital uncompensated care and patient experience: An instrumental variable approach', *Health services research*, 54(3), pp. 603-612.

Cassidy-Bushrow, A. E., *et al.* (2015) 'Time spent on the internet and adolescent blood pressure', *The Journal of school nursing*, 31(5), pp. 374-384.

Choi, Y.J. *et al.* (2020)'Cellular phone use and risk of tumors: Systematic review and meta-analysis', *International journal of environmental research and public health*, 17(21), pp. 8079.

Cotten, S.R. *et al.* (2014) 'Internet use and depression among retired older adults in the United States: A longitudinal analysis', *Journals of Gerontology Series B: Psychological Sciences and Social Sciences*, 69(5), pp. 763-771.

Currie, J. (2009) 'Healthy, wealthy, and wise: Socioeconomic status, poor health in childhood, and human capital development', *Journal of economic Literature*, 47(1), pp. 87-122.

Dessie, A. *et al.* (2018) 'Computer vision syndrome and associated factors among computer users in Debre Tabor Town, Northwest Ethiopia', *Journal of environmental and public health*.

Demir, Y.P. and Sümer, M.M. (2019) 'Effects of smartphone overuse on headache, sleep and quality of life in migraine patients', *Neurosciences Journal*, 24(2), pp. 115-121.

DiNardi, M., Guldi, M. and Simon, D. (2019) 'Body weight and Internet access: evidence from the rollout of broadband providers', *Journal of Population Economics*, 32(3), pp. 877-913.

Donati, D. *et al.* (2022) *Lost in the Net? Broadband Internet and Youth Mental Health.* IZA DP No. 15202.

D'Orazio, M. (2016) *Statistical Matching and Imputation of Survey Data with StatMatch.* Rome: Italian National Institute of Statistics.

Dutta, U. P., Gupta, H.and Sengupta, P. P. (2019) 'ICT and health outcome nexus in 30 selected Asian countries: Fresh evidence from panel data analysis', *Technology in Society*, 59.

Ekşioğlu, M. (2017) 'Musculoskeletal and visual symptoms among undergraduate students: Individual and computer-use-related risk factors and interference with academic performance', *International Journal of Industrial Ergonomics*, 60, pp. 26-34.

Forsman, A.K. and Nordmyr, J. (2017) 'Psychosocial links between Internet use and mental health in later life: a systematic review of quantitative and qualitative evidence', *Journal of Applied Gerontology*, 36(12), pp. 1471-1518.

Gholami, R. *et al.* (2010) 'Is ICT The Key to Development?', *Journal of Global Information Management*, 18, pp. 66–83.

Goodman-Bacon, A. (2021) 'Difference-in-differences with variation in treatment timing', *Journal of Econometrics*, 225(2), pp. 254-277.

Hamel, J.Y. (2012) 'ICT in the Human Development Dimensions of Health, Education and Income', *Indian Journal of Human Development*, 6(1), pp. 67-84.

Iqbal, K., Hassan, S.T. and Peng, H. (2019) 'Analyzing the role of information and telecommunication technology in human development: panel data analysis', *Environmental Science and Pollution Research*, 26(15), pp. 15153-15161.

Jorgenson, D. W. and Vu K. M. (2016) 'The ICT revolution, world economic growth, and policy issues', *Telecommunications Policy*, 40(5), pp. 383-397.

Karaman Aksentijevi´c, N., Jěži´c, Z. and Zaninovi´c, P. A. (2021) 'The Effects of Information and Communication Technology (ICT) Use on Human Development—A Macroeconomic Approach', *Economies*, 9(128). Available at: https://doi.org/10.3390/economies9030128.

Khovanova-Rubicondo, K. (2011) 'Evaluating ICT potential for improving health information quality in Africa', *IST-Africa Conference Proceedings*, pp. 1-8. IEEE.

Lancaster University. (2018). 'Why some older people are rejecting digital technologies', *ScienceDaily.* Retrieved from www.sciencedaily.com/releases/2018/03/180312091715.htm

Leena, K., Tomi, L. and Arja, R. (2005) 'Intensity of mobile phone use and health compromising behaviours—how is information and communication technology connected to health-related lifestyle in adolescence?', *Journal of adolescence*, 28(1), pp. 35-47.

Mars, B. *et al.* (2020) 'Prospective associations between internet use and poor mental health: A population-based study', *PLoS one*, 15(7).

Murphy, K.M. and Topel, R.H. (2006) 'The value of health and longevity', *Journal of Political Economy*, 114(5), pp. 871-904.

Mithas, S., Khuntia, J. and Agarwal, R. (2009) 'Information technology and life expectancy: A country-level analysis', *ICIS 2009 Proceedings*, pp. 146.

Näsi, M., Räsänen, P. and Sarpila, O. (2012) 'ICT activity in later life: Internet use and leisure activities amongst senior citizens in Finland', *European Journal of Ageing*, 9(2), pp. 169-176.

National Statistical Office of Thailand (2021) *Health and Welfare Survey (HWS).*

National Statistical Office of Thailand (2021) *ICT Using Survey (ICTH).*

Nuvolari, A. (2020) *The ICT revolution in historical perspective.* Growth Welfare Innovation Productivity Working Paper.

Pfeffer, F.T. and Schoeni, R.F. (2014) 'Intergenerational transmission of well-being', *Focus*, 31(1).

Puhani, P.A. (2012) 'The treatment effect, the cross difference, and the interaction term in nonlinear "difference-in-differences" models', *Economics Letters*, 115(1), pp. 85-87.

Rajaobelina, L. *et al.* (2021). 'Not all elderly are the same: fostering trust through mobile banking service experience', *International Journal of Bank Marketing*, 39(1), pp. 85-106.

Rodriguez-Alvarez, A. and Rodriguez-Gutierrez, C. (2018) 'The impact of health on wages: evidence for Europe', *The European Journal of Health Economics*, 19(8), pp.

1173-1187.

Sánchez, E. (2006) *What effects do mobile phones have on people's health*. Copenhagen: WHO Regional Office for Europe.

Saporta, G. (2002) 'Data fusion and data grafting', *Computational Statistics Data Analysis*, 38(4), pp. 465-473.

Shih, Y.W. *et al.* (2020) 'The association between smartphone use and breast cancer risk among Taiwanese women: a case-control study', *Cancer Management and Research*, 12, pp. 10799.

Shin, M. *et al.* (2022) 'Online media consumption and depression in young people: A systematic review and meta-analysis', *Computers in Human Behavior*, 128, pp. 107129.

Somcharoen, Y. and Dickie, J. (2019) 'Factors that affect office workers who work continuously for a long time that have an effect on office syndrome. international college suan sunandha rajabhat university', *International Scientific Conference on Innovations in Digital Economy*, pp. 54-57.

Sueki, H. (2013) 'The effect of suicide-related Internet use on users' mental health', *Crisis*, 34(5), pp. 348–353.

Strauss, J. and Thomas, D. (1998) 'Health, nutrition, and economic development', *Journal of economic literature*, 36(2), pp. 766-817.

Thomée, S., Härenstam, A. and Hagberg, M. (2012) 'Computer use and stress, sleep disturbances, and symptoms of depression among young adults–a prospective cohort study', *BMC psychiatry*, 12(1), pp. 1-14.

Văidean, V.L. and Achim, M.V. (2022) 'When more is less: Do information and communication technologies (ICTs) improve health outcomes? An empirical investigation in a non-linear framework', *Socio-Economic Planning Sciences*, 80(C).

Wooldridge, J. M. (2022) *Simple Approaches to Nonlinear Difference-in-Differences with Panel Data*. Available at SSRN: https://ssrn.com/abstract=4183726.

2.7 Appendix

Table A2.1: Variable definitions and summary statistics (1996–2019)

Variable	Definition	Mean	Standard deviation	Minimum	Maximum	No. of individuals
Dependent Variables						
health	Dummy variable that equals to 1 if individual has health problem and 0 if others	0.110	0.312	0	1	436,898
physical	Dummy variable that equals to 1 if individual has physical illness and 0 if others	0.108	0.310	0	1	436,898
muscle	Dummy variable that equals to 1 if individual has muscle inflammation and 0 if others	0.027	0.163	0	1	436,898
pressure	Dummy variable that equals to 1 if individual has blood pressure and 0 if others	0.068	0.251	0	1	436,898
vision	Dummy variable that equals to 1 if individual has vision problem and 0 if others	0.002	0.043	0	1	436,898
mental	Dummy variable that equals to 1 if individual has mental illness and 0 if others	0.021	0.142	0	1	436,898
stress	Dummy variable that equals to 1 if individual has stress, migraine, poor sleep and 0 if others	0.018	0.134	0	1	436,898
depress	Dummy variable that equals to 1 if individual has depression and 0 if others	0.002	0.049	0	1	436,898
Explanatory Variables						
first_treat	The first year that individual adopt ICT	1636.414	779.749	0	2019	436,898
days	Number of days of ICT use per month (day)	4.886	10.560	0	30	436,898
hours	Number of hours of ICT use per day (hour)	1.119	2.3549	0	12	436,898
work	Dummy variable that equals to 1 if individual use ICT for work and 0 if others	0.127	0.333	0	1	436,898
commu	Dummy variable that equals to 1 if individual use ICT for communication including email, video call, chat and 0 if others	0.112	0.316	0	1	436,898
soc	Dummy variable that equals to 1 if individual use ICT for social media, share information and 0 if others	0.129	0.335	0	1	436,898
ent	Dummy variable that equals to 1 if individual use ICT for entertainment including watch movies, listen to music, play game and 0 if others	0.125	0.331	0	1	436,898
learn	Dummy variable that equals to 1 if individual use ICT for study, e-learning, e-book, search engine and 0 if others	0.133	0.339	0	1	436,898
commerce	Dummy variable that equals to 1 if individual use ICT for e-commerce and 0 if others	0.067	0.249	0	1	436,898
bank	Dummy variable that equals to 1 if individual use ICT for internet banking, mobile banking, e-wallet and 0 if others	0.025	0.155	0	1	436,898
gender	Dummy variable that equals to 1 if individual is male and 0 if others	0.510	0.500	0	1	436,898
age	Age of individual (year)	44.422	12.170	13	88	436,898
smoking	Dummy variable that equals to 1 if individual smoke and 0 if others	0.235	0.424	0	1	436,898
alcohol	Dummy variable that equals to 1 if individual consume alcohol beverage and 0 if others	0.353	0.478	0	1	436,898

Table A2.2: Effect of ICT adoption on physical health

Cohort/Event/Time	**Simple margin**	**Cohort-specific effects**	**Event study**	**Calendar time effects**
	-0.0067**			
	(0.0034)			
2001/e=0		0.001	-0.016***	-0.002
		(0.008)	(0.002)	(0.004)
2003/e=1		-0.018***	0.005	-0.012**
		(0.006)	(0.0039)	(0.005)
2005/e=2		0.005	-0.013***	-0.007
		(0.0047)	(0.0036)	(0.004)
2007/e=3		0.0062	-0.010***	-0.0004
		(0.005)	(0.0047)	(0.003)
2009/e=4		-0.0019	-0.0099***	-0.009*
		(0.0055)	(0.0029)	(0.005)
2011/e=5		-0.019***	0.0016	-0.006
		(0.006)	(0.0053)	(0.004)
2013/e=6		-0.007	-0.0085**	-0.009*
		(0.0071)	(0.0034)	(0.005)
2015/e=7		-0.032***	-0.0055	0.002
		(0.0073)	(0.0068)	(0.005)
2017/e=8		-0.046***	-0.0072	-0.010**
		(0.0067)	(0.0051)	(0.005)
2019/e=9		-0.039***	0.017**	-0.0105**
		(0.0076)	(0.0074)	(0.005)
Controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	436,898	436,898	436,898	436,898

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

Table A2.3: Effect of ICT adoption on mental health

Cohort/Event/Time	Simple margin	Cohort-specific effects	Event study	Calendar time effects
	0.002			
	(0.001)			
2001/e=0		0.001	-0.0005	-0.001
		(0.002)	(0.001)	(0.002)
2003/e=1		0.002	-0.001	-0.0003
		(0.0018)	(0.003)	(0.0027)
2005/e=2		0.0002	0.0009	-0.0013
		(0.0017)	(0.0017)	(0.0022)
2007/e=3		0.0055***	0.0005	0.0012
		(0.0016)	(0.0025)	(0.0018)
2009/e=4		0.0035***	0.0042***	0.0009
		(0.0017)	(0.0014)	(0.0023)
2011/e=5		0.0014	0.0018	0.0028
		(0.0017)	(0.0024)	(0.0018)
2013/e=6		0.003	0.0023	0.0007
		(0.002)	(0.0015)	(0.0016)
2015/e=7		0.0033	-0.0015	0.0043***
		(0.0022)	(0.0027)	(0.0013)
2017/e=8		0.0002	0.003	0.0033***
		(0.002)	(0.0018)	(0.0014)
2019/e=9		0.0016	0.0044**	0.0018
		(0.0024)	(0.0024)	(0.0014)
Controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	436,898	436,898	436,898	436,898

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

Table A2.4: Effect of ICT adoption on health in different age cohorts

Cohort/Event/Time	Simple margin	Cohort-specific effects	Event study	Calendar time effects
Panel A Youth (13-24 years)				
	-0.006*			
	(0.003)			
2001/e=0		-0.006	-0.006***	-0.001
		(0.006)	(0.002)	(0.004)
2003/e=1		-0.012*	-0.004	-0.011*
		(0.005)	(0.004)	(0.005)
2005/e=2		-0.006	-0.003	-0.009**
		(0.004)	(0.004)	(0.004)
2007/e=3		0.004	-0.011**	-0.005*
		(0.005)	(0.005)	(0.003)
2009/e=4		-0.003	-0.001	-0.014**
		(0.006)	(0.003)	(0.006)
2011/e=5		0.008	-0.006	-0.008
		(0.006)	(0.005)	(0.005)
2013/e=6		0.004	-0.005	0.003
		(0.007)	(0.004)	(0.005)
2015/e=7		0.0009	-0.001	-0.002
		(0.008)	(0.007)	(0.006)

Continued on next page

Table A2.4 – *Continued from previous page*

Cohort/Event/Time	Simple margin	Cohort-specific effects	Event study	Calendar time effects
2017/e=8		-0.0006	-0.008	0.004
		(0.012)	(0.006)	(0.007)
2019/e=9		-0.031	0.001	-0.019
		(0.027)	(0.009)	(0.017)
Observations	190,387	190,387	190,387	190,387
Panel B Adults (25-59 years)				
	-0.002			
	(0.004)			
2001/e=0		0.003	-0.016***	-0.003
		(0.009)	(0.002)	(0.005)
2003/e=1		-0.012*	0.007*	-0.012
		(0.007)	(0.004)	(0.006)
2005/e=2		0.012**	-0.011***	-0.003
		(0.005)	(0.004)	(0.005)
2007/e=3		0.010*	-0.004	0.002
		(0.005)	(0.005)	(0.003)
2009/e=4		0.001	-0.008**	-0.004
		(0.006)	(0.003)	(0.006)
2011/e=5		-0.017***	0.003	-0.002
		(0.006)	(0.006)	(0.005)

Continued on next page

Table A2.4 – *Continued from previous page*

Cohort/Event/Time	**Simple margin**	**Cohort-specific effects**	**Event study**	**Calendar time effects**
2013/e=6		-0.005	-0.005	-0.005
		(0.007)	(0.004)	(0.004)
2015/e=7		-0.031***	0.0003	0.009*
		(0.007)	(0.007)	(0.005)
2017/e=8		-0.047***	-0.003	-0.006
		(0.006)	(0.005)	(0.005)
2019/e=9		-0.037***	0.029***	-0.005
		(0.008)	(0.008)	(0.005)
Observations	393,332	393,332	393,332	393,332
Panel C Elders (60 years and older)				
	0.009			
	(0.024)			
2001/e=0		-0.034	-0.008	-0.050
		(0.060)	(0.017)	(0.046)
2003/e=1		0.066	0.020	-0.010
		(0.187)	(0.031)	(0.073)
2005/e=2		0.219*	0.096	-0.042
		(0.122)	(0.142)	(0.066)
2007/e=3		0.048	0.041	-0.014
		(0.081)	(0.040)	(0.039)

Continued on next page

Table A2.4 – *Continued from previous page*

Cohort/Event/Time	Simple margin	Cohort-specific effects	Event study	Calendar time effects
2009/e=4		0.042	-0.041	0.013
		(0.076)	(0.071)	(0.060)
2011/e=5		0.056	0.054	0.009
		(0.041)	(0.037)	(0.014)
2013/e=6		-0.002	0.154	-0.013
		(0.079)	(0.153)	(0.042)
2015/e=7		-0.008	0.028	0.092**
		(0.048)	(0.056)	(0.039)
2017/e=8		0.049	0.385**	0.032
		(0.039)	(0.180)	(0.031)
2019/e=9		-0.017	-0.054	0.006
		(0.027)	(0.064)	(0.022)
Observations	35,167	35,167	35,167	35,167
Controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

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

Table A2.5: Effect of ICT usage frequency on health in different age cohorts

	Physical illness			Mental illness	
	Muscle inflammation	Blood pressure	Vision problem	Stress/Migraine/ Poor sleep	Depression
Panel A Youth (13-24 years)					
Days	-0.0001				
	(0.003)				
		0.002			
		(0.002)			
			0.003		
			(0.010)		
				-0.005**	
				(0.002)	
					-0.0003*
					(0.005)
Hours	-0.005				
	(0.010)				
		-0.0004			
		(0.010)			
			-0.072		
			(0.048)		

Continued on next page

Table A2.5 – *Continued from previous page*

	Physical illness			**Mental illness**	
	Muscle inflammation	Blood pressure	Vision problem	Stress/Migraine/ Poor sleep	Depression
				-0.021**	
				(0.009)	
					0.031*
					(0.018)
Observations	17,647	16,351	1,323	22,272	3,631
Panel B Adults (25-59 years)					
	0.002*				
	(0.001)				
		0.001*			
		(0.0008)			
Days			-0.009*		
			(0.005)		
				-0.003**	
				(0.002)	
					-0.003
					(0.003)

Continued on next page

Table A2.5 – *Continued from previous page*

	Physical illness			Mental illness	
	Muscle inflammation	Blood pressure	Vision problem	Stress/Migraine/ Poor sleep	Depression
Hours	-0.001				
	(0.006)				
		0.004			
		(0.003)			
			-0.060**		
			(0.025)		
				-0.016**	
				(0.007)	
					0.011
					(0.013)
Observations	107,112	197,203	8,107	75,297	10,604
Panel C Elders (60 years and older)					
Days	-0.001*				
	(0.005)				
		-0.0006			
		(0.002)			

Continued on next page

Table A2.5 – *Continued from previous page*

	Physical illness			Mental illness	
	Muscle inflammation	Blood pressure	Vision problem	Stress/Migraine/ Poor sleep	Depression
			0.006		
			(0.012)		
				-0.006	
				(0.009)	
					-0.018
					(0.019)
	-0.035				
	(0.023)				
		-0.008			
		(0.012)			
Hours			0.040		
			(0.060)		
				-0.030	
				(0.042)	
					-0.078
					(0.113)
Observations	15,406	34,208	2,105	5,821	521
Controls	Yes	Yes	Yes	Yes	Yes

Continued on next page

Table A2.5 – *Continued from previous page*

	Physical illness			Mental illness	
	Muscle inflammation	Blood pressure	Vision problem	Stress/Migraine/ Poor sleep	Depression
Individual FE	Yes	Yes	Yes	Yes	Yes
Year FE	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 A2.6: Effect of ICT activities on health in different age cohorts

	Physical illness			Mental illness	
	Muscle inflammation	Blood pressure	Vision problem	Stress/Migraine/ Poor sleep	Depression
Panel A Youth (13-24 years)					
Working	0.079	0.187**	0.002	-0.045	0.321**
	(0.077)	(0.082)	(0.296)	(0.068)	(0.154)
Communication	-0.123	-0.134	0.818*	-0.120	-0.292*
	(0.106)	(0.099)	(0.443)	(0.104)	(0.177)
Social media	-0.301**	0.034	-0.452	-0.456***	-0.323
	(0.122)	(0.114)	(0.518)	(0.123)	(0.208)
Entertainment	0.133	-0.100	-0.545	0.040	0.023
	(0.097)	(0.098)	(0.452)	(0.094)	(0.186)
Learning	0.089	0.009	-0.148	0.169**	0.486***
	(0.088)	(0.089)	(0.349)	(0.081)	(0.162)
Commerce	-0.067	0.115	-0.231	-0.314**	-0.061
	(0.120)	(0.105)	(0.543)	(0.136)	(0.183)
Banking	-0.001	-0.047	0.537	-0.838***	-0.551**
	(0.169)	(0.135)	(0.654)	(0.262)	(0.235)
Observations	17,647	16,351	1,323	22,272	3,631

Continued on next page

Table A2.6 – *Continued from previous page*

	Physical illness			Mental illness	
	Muscle inflammation	Blood pressure	Vision problem	Stress/Migraine/ Poor sleep	Depression
Panel B Adults (25-59 years)					
Working	0.040	-0.048	-0.064	0.012	-0.032
	(0.043)	(0.029)	(0.185)	(0.049)	(0.104)
Communication	-0.051	-0.062*	-0.0002	-0.078	-0.132
	(0.057)	(0.036)	(0.251)	(0.070)	(0.124)
Social media	-0.139**	0.175***	-0.391	-0.522***	0.486***
	(0.060)	(0.037)	(0.262)	(0.076)	(0.133)
Entertainment	0.047	0.111***	-0.433**	0.045	0.330***
	(0.054)	(0.035)	(0.247)	(0.066)	(0.123)
Learning	0.093*	0.088***	0.325	0.131**	0.264**
	(0.050)	(0.032)	(0.209)	(0.058)	(0.112)
Commerce	-0.105*	-0.031	-0.079	-0.230***	0.043
	(0.064)	(0.038)	(0.290)	(0.085)	(0.124)
Banking	0.026	-0.077	0.252	-0.369***	-0.111
	(0.084)	(0.049)	(0.351)	(0.129)	(0.155)
Observations	107,112	197,203	8,107	75,297	10,604
Panel C Elders (60 years and older)					

Continued on next page

Table A2.6 – *Continued from previous page*

	Physical illness			**Mental illness**	
	Muscle inflammation	Blood pressure	Vision problem	Stress/Migraine/ Poor sleep	Depression
Working	-0.414**	-0.116	-0.500	-0.084	0.152
	(0.185)	(0.102)	(0.511)	(0.047)	(1.318)
Communication	-0.029	-0.026	0.903	-0.580	-1.264
	(0.215)	(0.111)	(0.700)	(0.523)	(1.608)
Social media	-0.040	0.007	-0.129	-0.672	1.096
	(0.203)	(0.107)	(0.554)	(0.451)	(1.037)
Entertainment	0.027	0.077	-0.439	0.352	-0.516
	(0.213)	(0.109)	(0.696)	(0.461)	(1.225)
Learning	-0.290	0.026	0.170	-0.459	-1.099
	(0.191)	(0.102)	(0.511)	(0.418)	(1.060)
Commerce	-0.177	-0.009	0.228	0.279	-0.655
	(0.272)	(0.131)	(0.777)	(0.582)	(1.375)
Banking	-0.783**	-0.392**	0.552	2.238***	-
	(0.387)	(0.178)	(0.905)	(0.748)	
Observations	15,406	34,208	2,105	5,821	521
Controls	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes
Year FE	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.

Chapter 3

Coping with Crime via ICT (Against or Worsen?)

Abstract

Does social media use trigger or deter crime? This study implements the IV approach to examine the impact of social media on crime, combining the Crime Statistics and ICT Using Survey (ICTH) collected from the National Statistical Office of Thailand (NSO). The identification applied the ICT ownership variable as an IV to address endogeneity in social media. Social media can potentially decrease or foster crime, depending on crime statistics and the type of crime. Social media reduces reported crime rates while simultaneously stimulating convicted crime rates. The impacts in such directions affect offence related to life, body and sex and offence against property, also some specific crimes such as rape, drugs and gambling. However, social media has fueled both fraud and prostitution in reported and convicted crime rates. In a further study, the different results of using social media via different levels of high-speed internet are analysed. Using social media via high-speed internet has results consistent with the results of the main study. Meanwhile, different province sizes and average education levels influence social media use and crime differently. Policymakers may need to monitor social media use that leads to certain crimes according to the local context.

I wish to thank Professor Marco Francesconi and Dr Xiaoyu Xia for their valuable guidance, Police Colonel Chatikorn Srimuang for enlightening discussions on interpreting crime results and seminar participants at the University of Essex for helpful feedback.

3.1 Introduction

The digital age, also known as the information age, began with the introduction of computers and various technologies that enabled the rapid transfer of data and increased the breadth of knowledge circulation within the economy and society (Shepherd, 2004). Therefore, as technology becomes more knowledge-based and people's daily lives become more connected to it, the impact of the digital age on the economy and society will be immense. The beginning of the Internet was especially when people's activities and lifestyles changed from offline to online. For example, using e-mail instead of letters, accessing information through various websites, networking and communicating in social networks. This has resulted in widespread use and technology development. In addition, it has expanded widely into commercial activities, becoming a digital economy. Thailand is one country that considers using digital technology to drive economic growth (Chakpitak *et al.*, 2018). The government, therefore, has prepared a 20-year national plan for digital development for the economy and society (2018-2037). There has been continuous investment in ICT infrastructure. Because Thailand has become digitally connected over the past several years, the number of internet users in Thailand is expected to increase gradually. In 2021, Thailand had 85.27% internet users of population, ranked 60th worldwide and 19th in Asia (Theglobaleconomy, 2023).

In addition to the impact of ICT on outcomes in the contexts of economy, education, and health, as reported in the previous chapters, some studies have also found effects on fertility behaviour (Billari, Giuntella and Stella, 2019; Nie, Peng and Luo, 2023) and political participation (Larson *et al.*, 2019; Enikolopov, Makarin and Petrova, 2020). One of the significant concerns about the impact of ICT is crime. Although ICT has many positive impacts, these developments have a pessimistic side. Almost every advancement comes with an opportunity to use it for criminal purposes. Introducing each new ICT expands the range of criminal opportunities and potential victims (Srivastava, 2012). Wall (2001) has categorised different types of computer-related crimes or cybercrime: computer attacks, fraud from transactions, intellectual property infringement, pornography via the internet and harassment by internet use. The broader access to the internet, the greater the risk of becoming a victim of crime.

From the findings in Chapter 2, it seems that ICT has quite an impact on mental health, especially depression. In some studies, depression was positively associated with violent crime (da Silva and Menezes, 2015; Hawkes, 2015; Ozkan, Rocque and Posick, 2019). Moreover, social media is an ICT activity with a statistically significant greater impact than other activities. The question is whether social media can result in higher crime. However, social media might also be used to detect crimes and help reduce crime rates. Therefore, further examination of the impact of social media on forms of crime should be investigated. The study's results will contribute to stakeholders in policymaking to enhance national confidence and security.

At the provincial level, this study is analysed using Crime Statistics and an ICT Using Survey (ICTH) from NSO covering 2008 to 2019. To resolve endogeneity, the instrumental variable approach is employed in the specification. ICT ownership, an IV, is positively and strongly associated with social media.

Amid a situation where overall crime rates have increased, and social media use has expanded in various platforms. Social media has a statistically significant influence on crime rates, including offence related to life, body and sex and offence against property. Social media has resulted in a reduction in reported crime rates. However, it has increased convicted crime rates. Further analysis of specific crimes such as rape, drugs, and gambling yielded results in the same direction. As for fraud and prostitution, social media use has been found to increase the rate of crimes reported and convicted.

Moreover, high-speed internet for using social media creates different results according to the level of access. The results confirmed consistency with the main results when using social media via high-speed internet. While using social media in large provinces reduces reported crime, some convicted crime rates, such as fraud and gambling, appear to rise. Social media use among highly educated groups reduces reported crime but increases convicted crime in fraud. Thus, social media use in a heterogeneous context affects crime differently. One effect is to provide policy changes in 2012 and 2015. Social media use increased in some types of crime noticeably between 2008 and 2015, different from before the ICT Free Wi-fi policy was launched. After the Village Broadband Internet policy was implemented, crime rates were decreased. It seems social media deter crime in the latter.

There are two points based on the results that require interpretation. The negative impact of social media use on crime is a substitution effect. In addition, social media users monitor crimes among users, causing the reporting of crimes to decrease. While social media is a potential tool for some people to commit crimes, digital footprints are clear evidence to convict.

The remainder of this study proceeds as follows. Section 2 provides the related literature. Section 3 outlines the policy context and related events and describes the data used in the empirical analysis. Section 4 reports the social media effect on crime outcomes, followed by Section 5, which provides concluding remarks and policy implications.

3.2 Related Literature

3.2.1 Economics of crime

Crime is a major social problem because crime causes damage to both life and property of people in society. The number of crimes and severity reflect the people's quality of life and affect the country's development. From an economic perspective, Becker (1968) applied economic models to explain criminal behaviour to determine the optimal policies to combat illegal behaviour. The main idea is that the decision to commit a crime evaluates the difference between benefits and costs. Criminals are like any other person who decides to commit a crime. The expected benefits of committing a crime are compared with the expected punishment (cost). If the benefits outweigh the harm, it will be done. However, if the benefit is less than the penalty, they will not do it.

Furthermore, Economics of crime emphasises the impact of incentives on criminal behaviour and evaluates alternative opportunities to reduce crime (Freeman, 1999). For example, some studies explore the role of economic incentives in the labour market. It has been found that falling minimum wages leads to increased crime (Machin and Meghir, 2004; Draca and Machin, 2015). In addition, it was analysed that crime occurs because of unemployment, and it was indicated that unemployment positively influences crime (Altindag, 2012).

3.2.2 The impact of ICT on crime

On the one hand, the internet provides new channels for hazardous or criminal behaviour. Also, it creates new opportunities for criminal activity, allowing offenders to find new ways of dealing with their victims and providing a boundless space for crime. That is the effect of transformations caused by the internet that has resulted in crime (Wall, 2015). Such transformations are due to the following key features of the internet: global, instantaneous, intrinsically transborder, digital network, and enables automated data processing (Koops, 2010). That becomes an online crime system and industry unlike any other. The public and private sectors face challenges in controlling the problem, especially the significant cost of crime prevention (Moore, Clayton and Anderson, 2009).

Social media is one of the most popular platforms for using the internet and, therefore, is an area that attracts cybercrime. A study in the United Kingdom reported a sevenfold increase in social media-related crimes just four years after Facebook launched (LawTeacher, 2013). There are empirical studies indicating the adverse effects of the internet. Internet use has dramatically increased reported, charged and convicted sexual crimes (Bhuller et al., 2013). Additionally, a study investigated a link between anti-refugee sentiment on social media and hate crimes against refugees in a case study in Germany (Müller and Schwarz, 2021). Social media can act as a propagation mechanism for violent crime, which may drive some offenders to commit acts of violence beyond their boundaries.

There is concern among some studies about the impact of ICT on specific groups of people, especially vulnerable groups such as young people. Young people are more likely to become victims of cybercrime, whether it be bullying, fraud, harassment, defamation or crime online (Oksanen and Keipi, 2013; Srivastava, 2012). Social media and digital games are internet platforms that young people like to access and have the potential to develop cyber violence that may eventually lead to suicide attempts or suicide intentions (Alotaibi and Mukred, 2022).

On the other hand, new technologies can be employed to prevent violence and conflict. Some countries in Latin America have used online platforms to develop databases and maps to help reduce murder rates (Mancini and O'Reilly, 2013). Areas with high crime rates, such as Africa, where access to ICT is expanding, have generated new opportunities to fight crime. Using the internet to connect communities and police, they can be alerted to anticipated threats and gain protection (Livingston, 2013). Moreover, there is evidence from some studies that social media plays a vital role in detecting crime rates, thereby reducing them remarkably. Vo *et al.* (2020) proved this by comparing Twitter data with actual crime data, and the analysis yielded coincident results, helping to detect crime patterns and capture real-time crime rates easily. This is consistent with the study by Wang *et al.* (2019) investigating the relationship between crime data and drug-related tweets. Thus, the results provide preliminary evidence that social media data could be applied as a supplemental tool in crime monitoring and prediction.

An empirical study by Asongu *et al.* (2019) used data from 148 countries to assess the association between Facebook penetration and violent crime. The result found a negative relationship that could be clarified as social media platforms being mechanisms that create friendly interactions. In addition, there is ideological moderation, thus helping to alleviate violence. Meanwhile, Diegmann (2019) studies the impact of high-speed internet on sexual crimes in Germany. The results show a substitution effect of child sexual abuse and internet availability. A possible implication is that high-speed internet has an advantage in uploading and downloading activities that require consumption, such as violent media or pornography. The internet has also replaced other activities at home. Therefore, sexual crimes will decrease because there will be less personal contact.

In summary, it seems that ICT, mainly social media activities, impacts crime both in terms of encouraging more violent crime and as a tool to help combat crime. Despite widespread concerns highlighted by the media about ICT misuse and its adverse effects, the overall impact of ICT policies also reveals substantial benefits for the economy and society. In the context of Thailand, coping with crimes via ICT should be investigated to improve ICT policies that align with the country's situation.

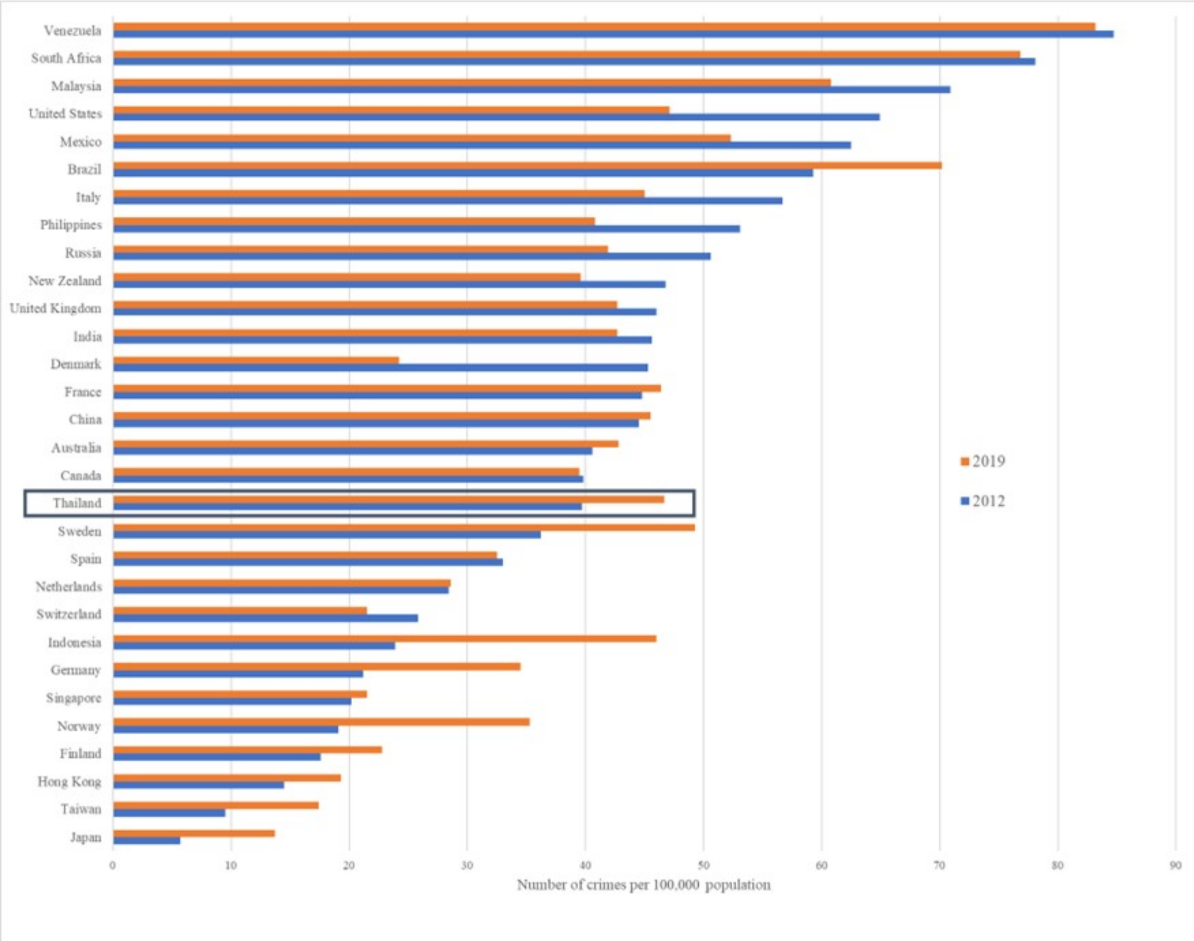
3.3 Background and Empirical Strategy

Crime is a problem in society that is dangerous to property and life. Statistics on crime rates worldwide show that crime has increased in many areas (Figure 3.1). Although the number in some regions has decreased, it is becoming more severe and complicated. Crime and safety are essential factors that may affect a country's social, economic, and political stability. The overall crime rate in Thailand was 46.70 in 2019, an increase of 17.63% from 2012.

Since the internet has played a role in daily life, computers and communication systems are used often. At the same time, some people use information communication technology in inappropriate ways. Cyber-related crimes are, therefore, a danger that Thailand must inevitably face. The government recognises the importance of maintaining cyber security and has therefore issued the Computer Crime Act 2007, which improved according to the situation until recently issuing the Cyber Security Act 2019. In addition to the government having legal tools to detect wrongdoing, the public also helps to monitor by reporting incidents through social media.

Social media is considered a new media. It increasingly influences people's percep-

Figure 3.1: Crime rate around the world

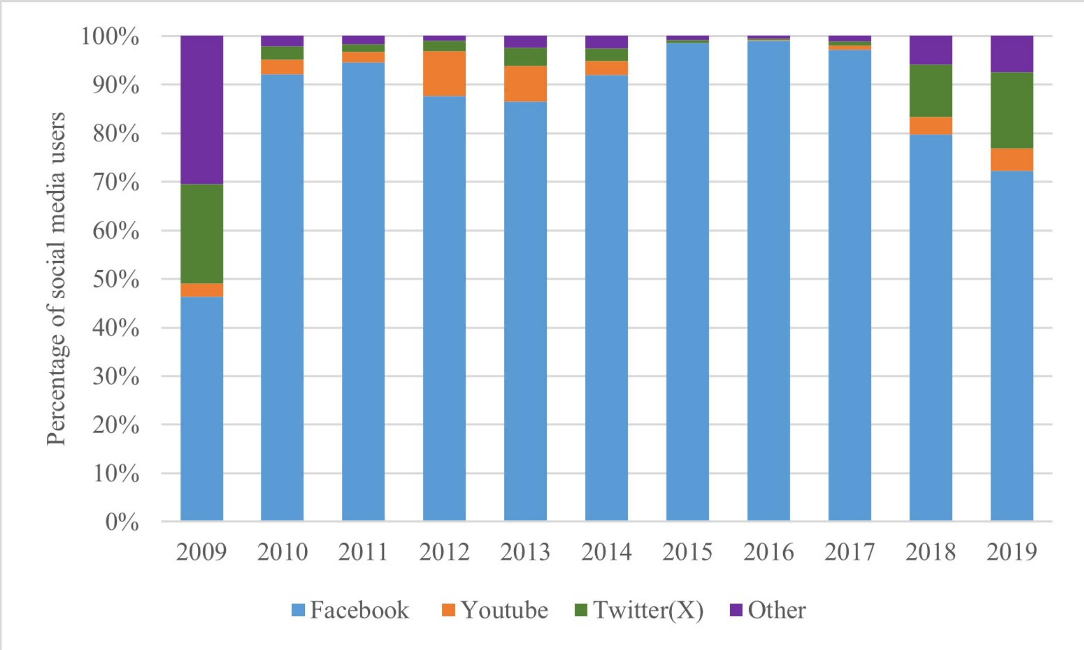


Source: numbeo (2023).

tions, attitudes, and behaviours. Advances in ICT have enabled social media to reach the audience conveniently, quickly, and immediately. The social media penetration rate has continuously increased over the past years. The number of social media users in Thailand was around 49.88 million (71.64%) in 2019 (Statista, 2023).

Due to increased ICT penetration rates, particularly on the internet, Thai people have become more active online through various platforms. Facebook is the most popular social media platform. Despite its popularity, the number of Facebook users is expected to decline. Platforms that are becoming more popular include Twitter(X), as shown in Figure 3.2.

Figure 3.2: Comparing the social media use by platform



Source: Statcounter Global Stats (2023).

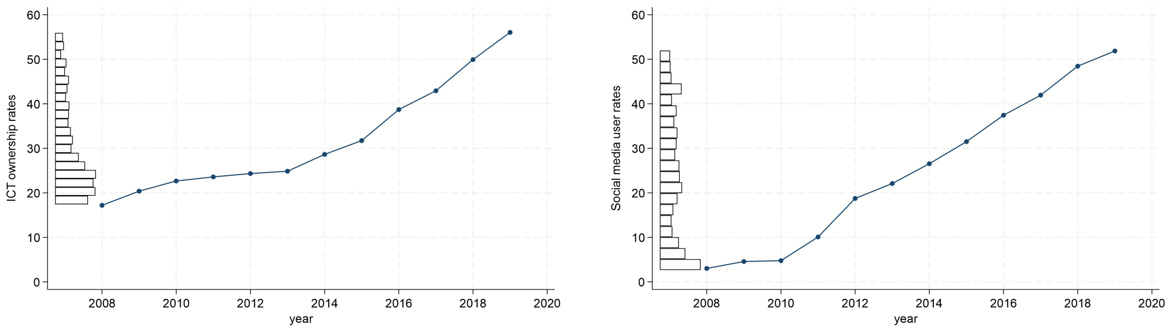
3.3.1 Data

The data used in this study between 2008 and 2019 were collected from Thailand's National Statistics Office (NSO). The data set is combined Crime Statistics sourced from the Royal Thai Police and ICT Using Survey (ICTH) covering 77 provinces. In addition, the administrative data by province are gathered for control variables. As one of the 77 provinces, namely Bueng Kan, was established in 2011, the data of this province is included in the data of its former sibling province, and thus, the final data set includes only 76 provinces. In total, about 912 observations are used in the study. Variable definitions and descriptive statistics on all variables used are displayed in Appendix Table A3.1.

ICTH provides household and individual data on the ICT usage behaviour of individuals and the use of ICT devices in households and sociodemographic characteristics, which have been surveyed annually since 2008. For Crime Statistics, many types of crime exist, which can be divided into three major categories: offence related to life, body and sex, offence against property and offence in which government is the victim or victimless crime. The offence related to life, body and sex includes homicide, assault, rape and sexual assault. At the same time, the offence against property includes robbery, burglary, embezzlement, and arson. The offence in which the government is the victim or victimless crime refers to drugs, gambling, prostitution, pornography, and possession of weapons.

The vital variables used in the analysis are social media penetration rates, calculated from the number of individuals using social media in each province for each year and ICT ownership rates, calculated from the number of individuals owning computers or mobile phones and accessing the internet. Figure 3.3(i) displays the overall mean ICT ownership rate and the distribution of ICT ownership rates across provinces between 2008 and 2019. There is considerable variation, both across provinces and over time. Figure 3.3(ii) displays the distribution and averages of social media user rates across provinces between 2008 and 2019. Social media use has increased over time, mainly after 2010.

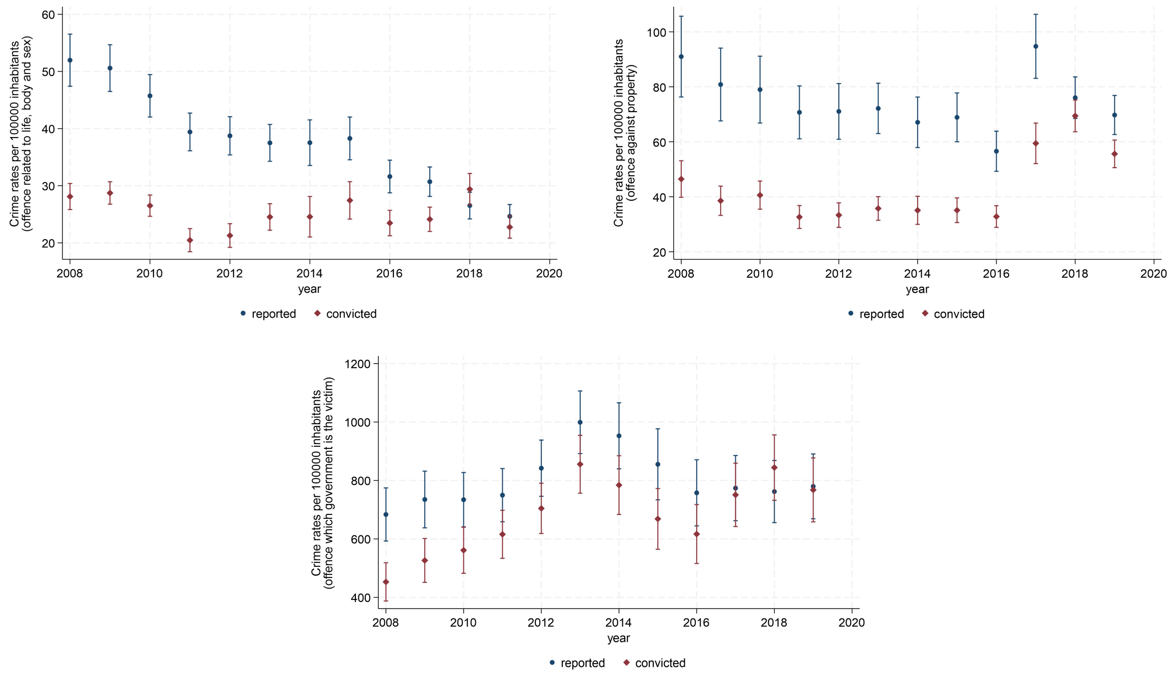
Figure 3.3: ICT ownership rates and social media user rates, averages, and distribution, 2008-2019



(i) (ii)

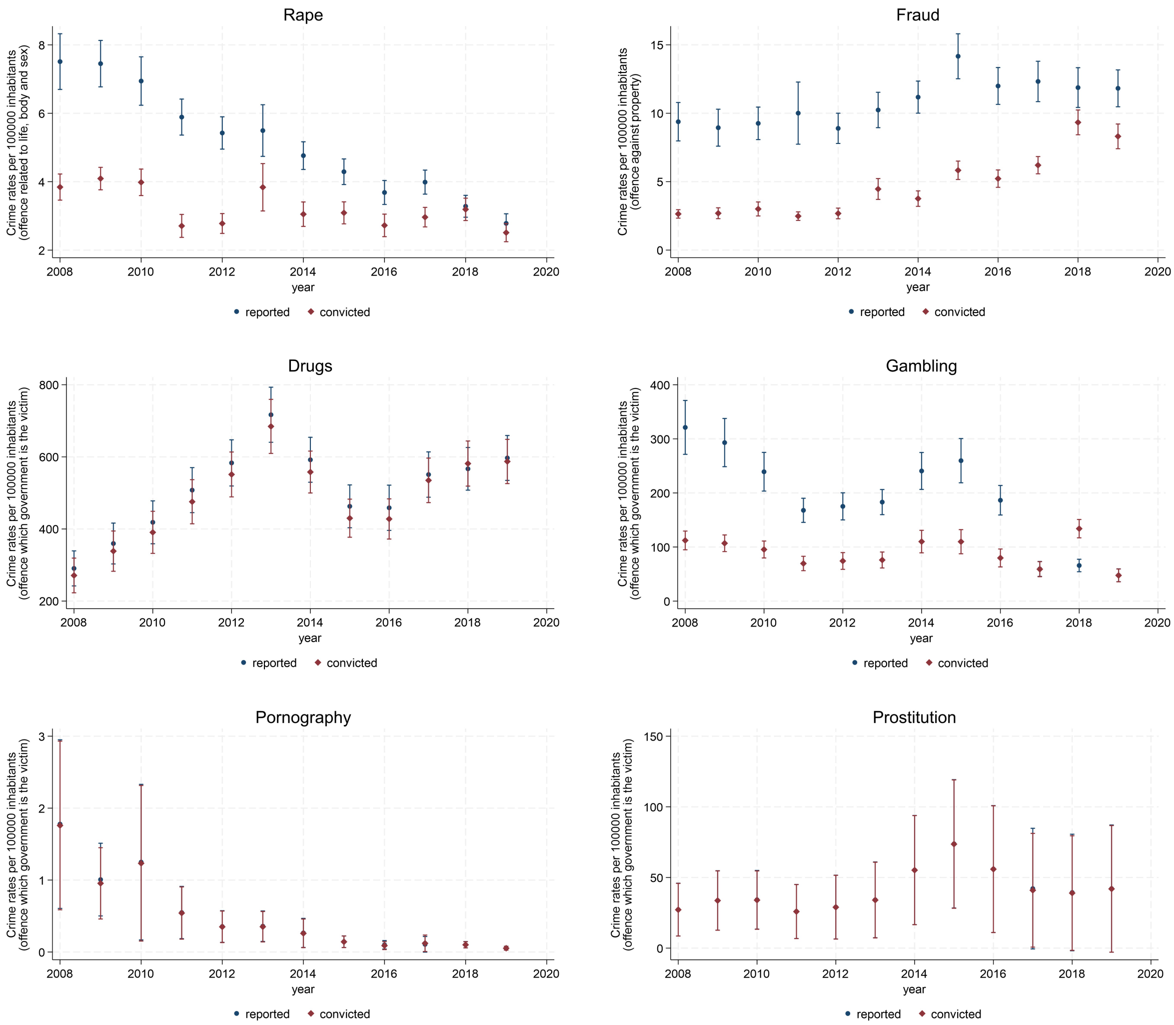
The binscatter can illustrate the difference between outcome variables, reported and convicted crime rates of provinces (Figures 3.4 and 3.5). The reported crimes have more cases than convicted crimes, especially a broader gap in the first period. Overall, offences related to life, body and sex are on a decreasing trend, while offences against property and victimless crimes appear to be on the increase. The study also considered deeper data on specific crimes that are likely associated with social media use, including rape, fraud, drugs, gambling, pornography and prostitution. Some crime rates appear to be reduced, such as rape and pornography. In contrast, fraud and drugs are apparent increases in cases.

Figure 3.4: Crime rate comparison with reported and convicted crime, 2008-2019



The percentage of provinces with social media user rates classified by level of high-speed internet is shown in Figure 3.6. In the early stages, there was a tiny gap between social media penetration rates in low high-speed internet rates and high high-speed internet rates. Later, the gap became more expansive and has continued to widen. The data reflects that high-speed internet accessibility influences the level of social media use. By adopting the United Nations classification of cities defined by population sizes (2019), this study classified 21 Thailand's provinces with more than 1 million inhabitants as large provinces. The gap between provinces in terms of social media usage is not that great, however, larger provinces have higher social media usage rates than smaller provinces. The comparison of social media users' education levels showed a similar trend to the comparison of high-speed internet users, with provinces with higher average levels of education using social media more than provinces with lower average levels of education.

Figure 3.5: Specific crime rate comparison with reported and convicted crime, 2008-2019

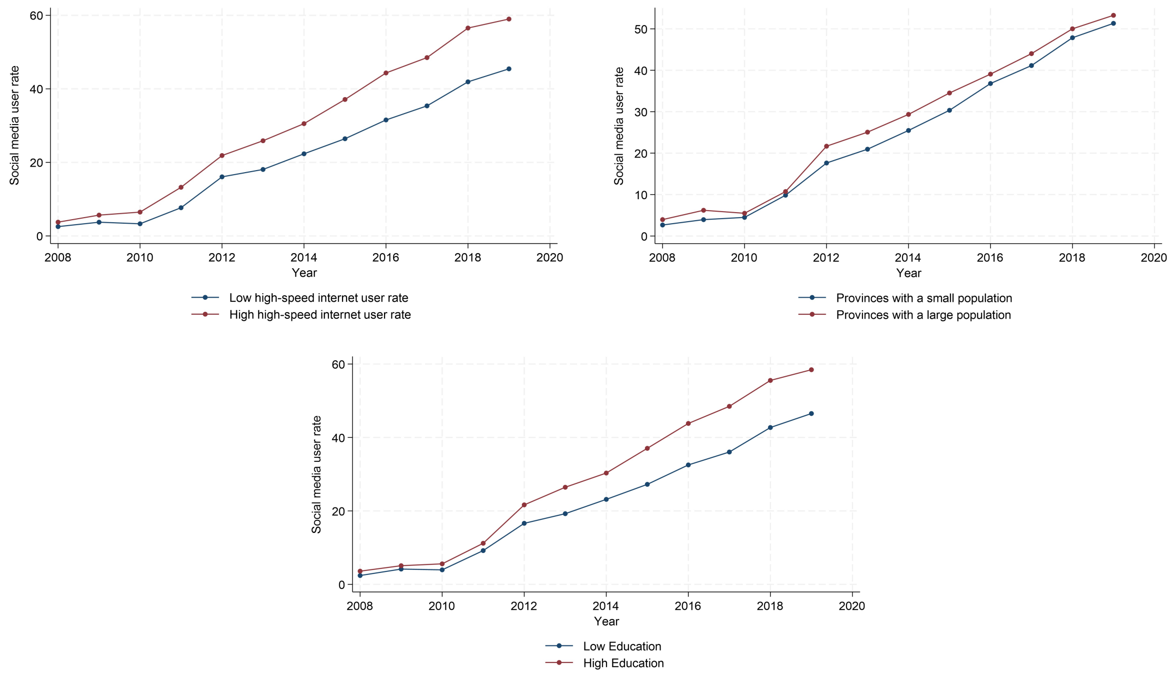


3.3.2 Research Methods

Since the data used in this study is panel data, the two-way fixed effects regression models widely used for causal inference with longitudinal or panel data are applied to adjust for unobserved unit-specific and time-invariant confounders simultaneously.

The main hypothesis in this study is that social media activities have an impact on crime. This strategy can be generalized to the framework in order to estimate the following model for all outcome variables considered the main baseline specification:

Figure 3.6: The social media user rate by high-speed internet level, province size and education level, 2008-2019



$$Crime_{pt} = \alpha + \beta_p + \gamma_t + \delta Socialmedia_{pt} + \omega X'_{pt} + \varepsilon_{pt} \tag{3.1}$$

where $Crime_{pt}$ is the outcome of province p at time t, β_p is a province fixed effect, γ_t is a year fixed effect, $Socialmedia_{pt}$ is the proportion of social media users of province p at time t , X'_{pt} a vector of control variables, and ε_{pt} is a residual disturbance.

The outcome denoted $Crime_{pt}$, is crime rate calculated by dividing the total number of reported or convicted crimes of any kind by the total population, then multiplying the result by 100,000.

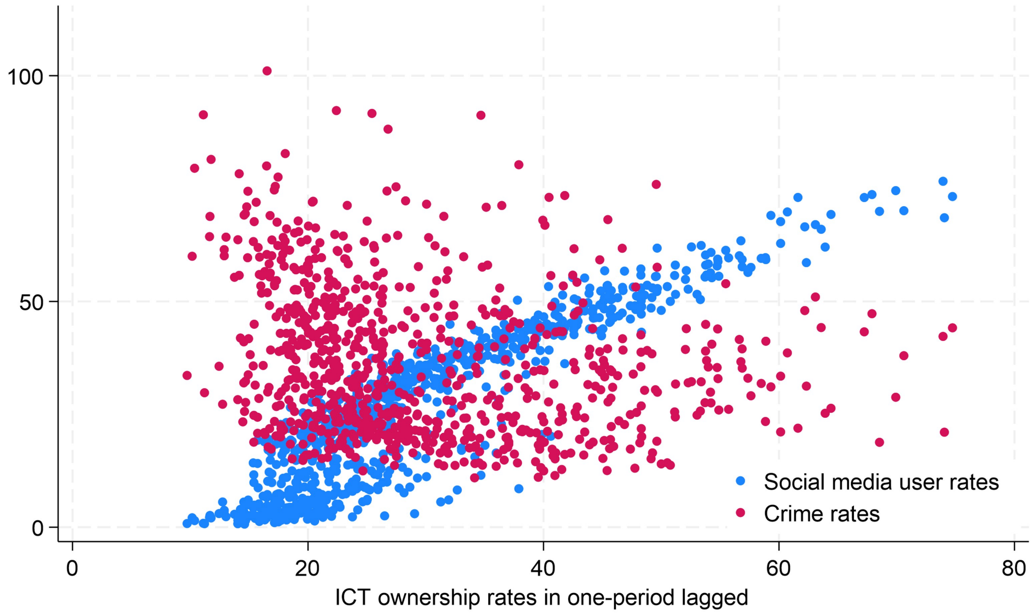
However, the TWFE estimates of equation (3.1) are likely biased, as the unobserved characteristics make people more or less likely to carry out social media activities. Another concern is reverse causality. For example, members of criminal gangs use social media to advertise their success from anti-normative lifestyles by carrying out illegal operations or using social media as a tool to promote illegal gambling or prostitution websites.

To identify a causal relationship between social media activities and crime rate, this study employs an FE two-stage IV model to mitigate concerns regarding the endogeneity of social media use. For the instrumental variables, some literature studies the impact of the internet on crime using the coverage rate (Bhuller *et al.*, 2013) and the public switched telephone network (PSTN) (Diegmann, 2019). However, such data in Thailand is quite limited and confidential. There are studies examining the impact of the internet on other outcomes using other interesting instrumental variables. Nie, Peng and Luo, 2023 applied the number of internet broadband access terminals (IBAT), while Lu and Kandilov (2021) considered smartphone ownership and Zhu, Li and Lin (2023) employed the one-period lagged internet use.

To control potential endogeneity, this study uses one instrument: ICT ownership rates in one-period lagged measured at the provincial level from the number of individuals owning computers or mobile phones and accessing the internet. Figure 3.7 shows the relationship between social media user rates and ICT ownership rates in one-period lagged, which clearly shows a strong positive relation. At the same time, the relationship between crime rates and ICT ownership rates is unclear, possibly a parallel pattern. This instrument can be shown to be exogenous to crime rate but closely linked with social media user rate. ICT ownership would likely increase social media accessibility and stimulate the possibility of using social media.

Two-stage least squared regression (2SLS) occurs in two phases. In the first stage, a predicted measure of social media activities will be estimated using ICT ownership rates in one-period lagged estimator as an instrument for social media use in the following regression model:

Figure 3.7: Social media user rates and crime rates, by ICT ownership rate in one-period lagged



$$Socialmedia_{pt} = \sigma + \phi_p + \rho_t + \tau ICT_{pt-1} + \theta X'_{pt} + \varepsilon_{pt} \tag{3.2}$$

where $Socialmedia_{pt}$ is a measure of social media activities of province p at time t, ϕ_p is a province fixed effect, ρ_t is a year fixed effect, ICT_{pt-1} is the ICT ownership rates by province in one-period lagged , X'_{pt} a vector of control variables, and ε_{pt} is a residual disturbance.

In the second stage, the predicted measure of $Socialmedia_{pt}$ obtained from equation (3.2) is used to estimate equation (3.3) in the following regression model:

$$Crime_{pt} = \alpha + \beta_p + \gamma_t + \delta \widehat{Socialmedia}_{pt} + \omega X'_{pt} + \varepsilon_{pt} \tag{3.3}$$

where $\widehat{Socialmedia}_{pt}$ represents the exogenous change in social media activity caused by the ICT ownership rate and is therefore uncorrelated with the error term.

All specifications include the controls for province characteristics: unemployment rate, poverty rate, consumer price index, year of schooling and population density.

3.4 Empirical Findings

The analysis of the effect of social media use on crime rates employs an instrumental variable strategy based on ICT ownership to control for potential endogeneity. Table 3.1 reports results from the 2SLS model given by equations (3.2) and (3.3) and the OLS model based on equation (3.1), also illustrating first-stage estimate and reduced form.

The first-stage IV estimates indicate a significant positive association between the instrument and social media use (Panel B), with an F-statistic around 32. Hence, concerns about weak identification issues do not apply, which contains a reference in Stock, Wright and Yogo (2002). When considering the second estimation results from Panel A, the estimated coefficients associated with social media and crime (offence related to life, body and sex and offence against property) are significantly negative in the reported crime rate and positive in the convicted crime rate. While the offence in which the government is the victim obtains the same sign results but is not statistically significant. Social media use may appear to reduce the reported crime rate but increase the convicted crime rate. The OLS regressions, without addressing the reverse causality problem between social media use and crime, obtained primarily similar results, but the effect sizes were smaller.

Table 3.2 consists of six sets of specifications that show findings based on the specific outcome variables: rape, fraud, drugs, gambling, pornography, and prostitution.

Table 3.1: Effect of social media on major categories crime

	Offence related to life, body and sex		**Offence against property**		**Offence which government is the victim**	
	reported	convicted	reported	convicted	reported	convicted
Panel A 2SLS and OLS						
IV: *soc*	-0.494***	0.327***	-1.380***	0.244	-5.339	0.952
	(0.123)	(0.112)	(0.343)	(0.215)	(4.180)	(3.919)
OLS: *soc*	-0.140**	0.132**	-1.017***	-0.003	-5.968***	-3.441*
	(0.064)	(0.057)	(0.182)	(0.111)	(2.180)	(2.015)
Panel B First stage						
ict_{t-1}			0.511***			
			(0.029)			
Panel C Reduced form						
ict_{t-1}	-0.252***	0.167***	-0.705***	0.125	-0.273	0.487
	(0.061)	(0.057)	(0.175)	(0.109)	(2.143)	(2.001)
R^2 (2SLS)	0.105	0.001	0.159	0.019	0.071	0.124
F -Statistic (first stage)			32.87			
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	836	836	836	836	836	836

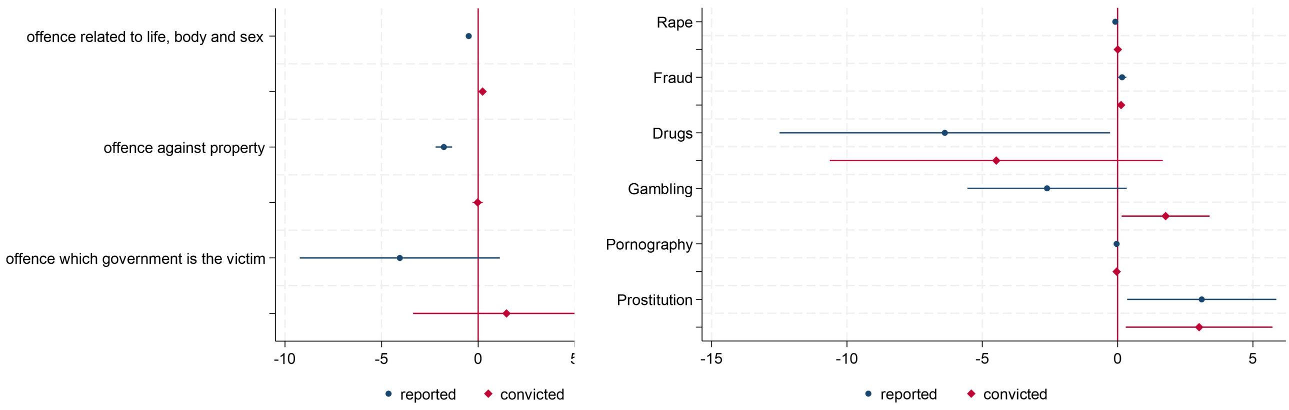
Notes: Each pair of rows reports the coefficient estimate and the associated standard error in parenthesis. $***$, $**$ and $*$ denote statistical significance at the 1%, 5% and 10% significance levels, respectively.

The impact of social media on reported rape and drugs is significantly negative. A 1% point increase in social media use causes a decrease in the reported rape crime rate of 0.09 and a decrease in the reported drug crime rate of 6.38 per 100,000 inhabitants. Meanwhile, social media seems to have resulted in an increase in fraud and prostitution, including reported and convicted crime rates. In the case of gambling, the estimated coefficients associated with social media and convicted gambling crime rate are significantly positive. In contrast, another reported gambling outcome is affected in the opposite sign.

The key coefficients are depicted in Figure 3.8 to clearly show how the expected values influenced outcomes in any direction and differ from 0 with statistical significance.

All three outcomes, including offence related to life, body and sex, offence against property and offence in which the government is the victim, tend to be affected similarly. When considering specific types of crimes in depth, it was found that the impact of social media use is different for different crime formats.

Figure 3.8: Estimated coefficients of social media on each crime outcome



(i) (ii)

Robustness Check

To check the robustness of the main results, an alternative estimation model is employed to increase the confidence in the IV results further using the first difference model as an estimator to eliminate the unobserved effect for panel data (Wooldridge, 2010). The coefficient of interest in the first-difference specification indicates the relationship between changes in social media use and changes in crime rates within the province over time. To mitigate the associated endogeneity biases with a two-step process, the first-difference instrumental variables (FDIV) approach is proposed and shown in the results in Table 3.3. The results were broadly consistent with the main study methods, especially the statistically significant values.

Heterogeneity analysis

To provide more in-depth perspectives on the association between social media use and crime, this section performs heterogeneity analyses by high-speed internet user rate, province size and education level using FE-IV estimates. Tables 3.4 and 3.5 show the results of IV estimates by different province attributes.

Because the use of social media is related to internet access, which has different levels of internet speed, in some areas, people may have more access to high-speed internet. One issue that should be studied further is that differences in internet speed levels may produce different results. Regarding Table 3.4, using social media with high-speed internet showed significant negative coefficients across reported crime rates. In comparison, those with low access to high-speed internet decreased reported crime rates as well but had a less significant effect size. However, the effect was reversed on convicted crime rate outcomes in low-access high-speed internet areas. It seems that using social media via high-speed internet can help monitor crimes and reduce them. This is consistent with some study findings in Table 3.5 that the estimated coefficients are significantly negative for reported crime rates in rape, drugs and pornography. However, some crimes, such as fraud and prostitution, have seen the use of social media via high-speed internet as a tool to encourage people to commit crimes, both reported and convicted crime rates.

Crime rates are generally higher in big cities than in smaller cities, depending on some factors, including population structure, economic conditions, and cost of crime (Glaeser and Sacerdote, 1999; Hipp and Kane, 2017). Internet use may also cause differences in the area. Different social media usage rates across province sizes affect stimulating or deterring crimes in the area. Social media has significantly reduced reported crime in both large and small provinces, with the effect size being somewhat greater in large provinces except rape crime. Meanwhile, in the case of convicted crime, small provinces may need to be careful about using social media, which increases crime, especially offence related to life, body and sex and offence against property that are statistically significant. However, the probability of being arrested may be higher in small provinces. When considering specific crimes, the convicted crime rates of concern in both large and small provinces were fraud and gambling, where social media use was found to increase the rate of such crimes, with larger provinces having higher results.

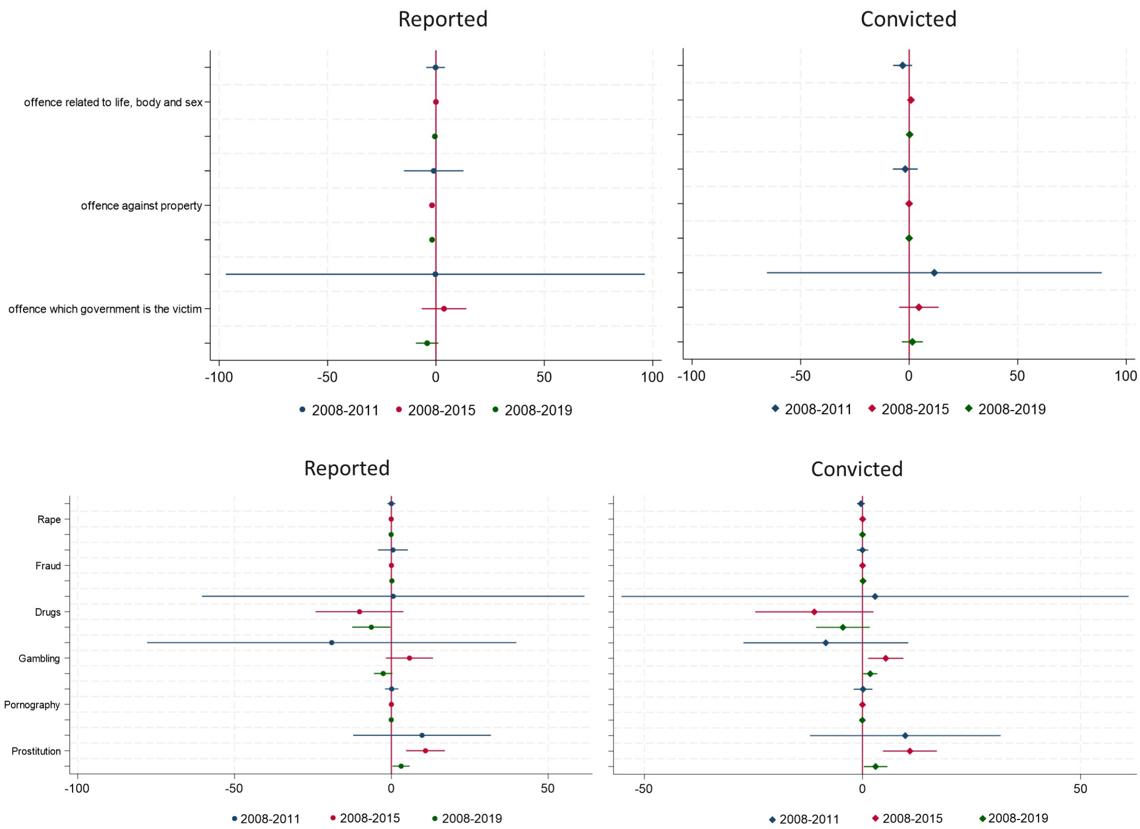
In the previous chapters, internet use was related to education in terms of learning and searching activities, increasing the education level. This chapter has divided provinces according to educational level based on the average year of schooling. Any province whose population has an average number of years of schooling higher than the national average is placed in the high education group, while the remaining provinces are in the low education group. From empirical studies, Bell, Costa, and Machin (2022) examined that education can reduce crime. Although Yildiz, Ocal and Yildirim (2013) found that education leads to increased crime, low education increases crime by approximately 3.5 times more than higher education. As Tables 3.4 and 3.5 in this study, social media use reduces reported crime in the high-educated group more than the low-educated group in offence related to life, body and sex and offence against property significantly. However, in some convicted crimes, social media use by highly educated groups causes a statistically significant increase in crime, especially fraud rates.

Policy effect

In order to gain insight into the implementation behind social media use and crime rate, this section aims to explain the policy effect, which changes in policy could also be related to effects. The data from 2008 to 2019, three central ICT policies were launched to promote the use of ICT by Thai people before 2008. The advent of smartphones and social media occurred slightly before 2008. Since then, there have been two further changes to ICT policy in 2012 and 2015, all promoting internet access: ICT Free Wi-Fi and Village Broadband Internet. That means the intensity of social media usage is likely to increase. As a result of policy changes, social media use may have different effects on crime. Two additional periods were analysed, 2008-2011 and 2008-2015, and the effects were compared as reported in Figure 3.9 and Appendix Table A3.2.

From 2008 to 2015, three years after implementing the ICT Free Wi-fi policy, social media use appears to have led to an increase in both reported and convicted crimes, excluding drug crimes. The most noticeable effects are on gambling and prostitution. While social media use was not very intensive at the beginning of the policy, it seems not to have influenced the increase in crime. When the Village Broadband Internet policy was in place, social media helped reduce reported crime. Although crime rates, such as gambling and prostitution, continued to increase, they were lower than in previous periods. However, social media use has driven a statistically significant increase in fraud.

Figure 3.9: Estimated coefficients of social media on crime in different periods.



3.5 Conclusions and Policy Implications

Regarding the insights gained from the study results in the previous chapters, there should be further in-depth study on the impact of ICT activities or channels of use. Social media is an ICT activity that creates a noticeable impact, especially on health, consistent with much of the literature. The adverse effects of ICT on mental health problems, according to the study results of Chapter 2, may be related to violent criminal activity. Therefore, this study examines the effect of ICT use on crime, an area of national security importance, focusing on social media activities.

The instrumental variable is applied in this study for endogeneity solutions in which ICT ownership is selected as an IV for social media use. The Crime Statistics and ICT Using Survey (ICTH) was collected from the National Statistical Office of Thailand (NSO) and used for provincial analysis.

The empirical study of the effects of social media use on crime rates found that the use of social media contributes to a statistically significant decrease in reported crime rates, including offence related to life, body and sex and offence against property. However, in the case of convicted crime rates, social media has provided an incentive to commit such crimes. There are different outcomes between specific types of crimes. Rape, drugs and gambling are affected by social media use in the same way. It reduces reported crimes but increases convicted crime rates. Meanwhile, the use of social media has fueled both reported crimes and convicted crime rates in cases of fraud and prostitution. The results were mostly consistent with the first-difference instrumental variables (FDIV) model for robustness check.

When considering the use of social media through different province attributes by heterogeneity analysis, it indicated that the levels of internet speed are likely to have significantly different results. Regarding reported crime rates, using social media via high-speed internet has helped reduce crime rates. In the case of convicted crime rates, it is a factor that drives the increase in crime with low access to high-speed internet. Rape, drugs, and pornography which are specific crimes, also have consistent negative impacts. Except for fraud and prostitution, the use of social media via high-speed internet has stimulated an increase in both reported and convicted crime rates. Seemingly, the high-speed internet leads to higher rates of criminal activities in certain types of crimes. The province size yields different results on the impact of social media use on crime. Social media use in large provinces reduced reported crime, and the effect was greater than in small provinces. Small provinces tend to use social media to cause convicted crimes. However, large provinces also have higher convicted crime rates due to the significant use of social media for fraud and gambling. Educational averages across areas have the potential to account for the differential impact of social media use on crime. Provinces with higher education levels are more likely to use social media to reduce reported crime. However, convicted rates in fraud were significantly higher with social media use among highly educated groups.

An additional analysis in this study considers the period of policy changes in 2012 and 2015 that likely influenced the use of social media in crime. From 2008 to 2011, social media use did not appear to increase crime significantly. Until the ICT Free Wi-fi policy was launched in 2012, social media use led to a marked increase in crime of some type between 2008 and 2015. When the Village Broadband Internet policy was implemented, social media use reduced crime, although some specific types of crimes had positive impacts but were lower than in previous periods.

As the results of this paper, it appears that social media is negatively associated with crime rates as a substitution effect, consistent with Kendall (2007) and Diegmann (2019), who use reported crime data to study the impact of internet usage on sexual offences. From another point of view, when the use of social media is widespread, there is scrutiny among users to the point that they do not dare to commit crimes, resulting in a decrease in reporting crimes. At the same time, the use of some social media platforms is quite fragile and may easily tempt or encourage people to commit crimes or become easy victims, causing the rate of conviction to increase. In addition, posting or doing anything on social media is considered a digital footprint, which is clear evidence of wrongdoing. Hence, policymakers should encourage citizens to help monitor the creative use of social media and detect suspicious platforms that may lead to crimes, such as online gambling and sexual services, via social media by considering the context of differences in the area.

Table 3.2: Effect of social media on specific crime

	Offence related to life, body and sex		**Offence against property**		**Offence which government is the victim**							
	Rape		Fraud		Drugs		Gambling		Pornography		Prostitution	
	reported	convicted	reported	convicted	reported	convicted	reported	convicted	reported	convicted	reported	convicted
Panel A 2SLS and OLS												
IV: *soc*	-0.085***	0.007	0.165**	0.129***	-6.384**	-4.482	-2.605*	1.775**	-0.037	-0.035	3.108**	3.013**
	(0.029)	(0.024)	(0.082)	(0.045)	(3.116)	(3.139)	(1.501)	(0.829)	(0.029)	(0.029)	(1.406)	(1.383)
OLS: *soc*	-0.047***	0.001	0.086**	0.085***	-6.505***	-6.083***	-1.116	0.969**	-0.051***	-0.049***	1.479**	1.446**
	(0.016)	(0.012)	(0.041)	(0.022)	(1.592)	(1.595)	(0.826)	(0.428)	(0.019)	(0.019)	(0.732)	(0.720)
Panel B First stage												
ict_{t-1}						0.511***						
						(0.029)						
Panel C Reduced form												
ict_{t-1}	-0.043***	0.004	0.085**	0.066***	-3.263**	-2.291	-1.332*	0.907**	-0.019	-0.018	1.589**	1.539**
	(0.015)	(0.012)	(0.042)	(0.023)	(1.605)	(1.616) (0.763)	(0.424)	(0.015)	(0.015)	(0.715)	(0.704)	
R^2 (2SLS)	0.057	0.056	0.145	0.117	0.008	0.006	0.007	0.008	0.009	0.009	0.034	0.035
F -Statistic (first stage)						32.87						
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province 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
Observations	836	836	836	836	836	836	836	836	836	836	836	836

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 3.3: Effect of social media on crime: Alternative specification, FDIV model

		Offense related to life, body and sex		**Offense against property**		**Offense which government is the victim**	
	Δ	reported	convicted	reported	convicted	reported	convicted
Panel A 2SLS							
IV: Δ *soc*		-0.037	0.667	-6.979**	-3.704*	3.178	-16.214
		(0.624)	(0.687)	(2.943)	(1.906)	(15.739)	(15.828)
	Rape	-0.185	0.012				
		(0.064)	(0.057)				
	Fraud			-0.163	0.033		
				(0.535)	(0.280)		
	Drugs					-32.233**	-33.154**
						(15.763)	(15.956)
	Gambling					-0.277	24.337***
						(21.362)	(8.100)
	Pornography					-0.124	-0.135
						(0.190)	(0.190)
	Prostitution					5.968	6.745
						(4.573)	(4.662)
Panel B First stage							
Δ ict_{t-1}		0.113***					
		(0.032)					
F -Statistic (first stage)		22.97					
Controls		Yes	Yes	Yes	Yes	Yes	Yes
Year FE		Yes	Yes	Yes	Yes	Yes	Yes
Observations		760	760	760	760	760	760

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 3.4: Effect of social media on major categories crime in different province attributes

IV: *soc*		**High-speed internet user rate**		**Province size**		**Education level**	
		High	Low	Large	Small	High	Low
Offense related to life, body and sex	reported	-0.902**	-0.825***	-0.854***	-0.263*	-0.575*	-0.557**
		(0.363)	(0.310)	(0.185)	(0.158)	(0.309)	(0.231)
	convicted	0.116	0.489**	0.054	0.532***	0.186	0.223
		(0.367)	(0.242)	(0.129)	(0.152)	(0.287)	(0.211)
Offense against property	reported	-1.828*	-1.732***	-2.727***	-0.739*	-2.682**	-0.545
		(0.993)	(0.636)	(0.570)	(0.426)	(1.166)	(0.362)
	convicted	-0.238	-0.221	-0.130	0.605**	-0.526	0.089
		(0.527)	(0.331)	(0.260)	(0.291)	(0.687)	(0.271)
Offense which government is the victim	reported	-19.719	-0.113	-13.797**	-5.204	8.638	-12.535**
		(15.356)	(7.509)	(6.821)	(5.248)	(12.742)	(6.074)
	convicted	-6.436	4.319	-8.082	0.169	17.375	-6.956
		(14.361)	(6.738)	(6.461)	(4.792)	(12.655)	(5.311)
First stage: ict_{t-1}		0.344***	0.315***	0.511***	0.507***	0.412***	0.371***
		(0.038)	(0.051)	(0.060)	(0.034)	(0.059)	(0.037)
F -Statistic		18.00	18.74	25.19	49.51	17.95	22.00
Controls		Yes	Yes	Yes	Yes	Yes	Yes
Province FE		Yes	Yes	Yes	Yes	Yes	Yes
Year FE		Yes	Yes	Yes	Yes	Yes	Yes
Observations		393	443	231	605	374	462

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 3.5: Effect of social media on specific crime in different province attributes

IV: *soc*		**High-speed internet user rate**		**Province size**		**Education level**	
		High	Low	Large	Small	High	Low
Rape	reported	-0.160*	0.018	-0.077**	-0.095**	-0.136**	-0.071
		(0.093)	(0.065)	(0.035)	(0.039)	(0.066)	(0.064)
	convicted	-0.020	0.082	0.023	0.011	0.012	-0.018
		(0.078)	(0.050)	(0.025)	(0.032)	(0.045)	(0.056)
Fraud	reported	0.099	-0.023	0.163*	0.204*	0.124	0.109
		(0.291)	(0.163)	(0.098)	(0.110)	(0.173)	(0.182)
	convicted	0.222	-0.043	0.238***	0.108*	0.284***	0.047
		(0.140)	(0.103)	(0.084)	(0.056)	(0.107)	(0.091)
Drugs	reported	-23.365**	-1.947	-11.982**	-5.602	1.759	-13.923***
		(11.024)	(5.918)	(5.450)	(3.889)	(9.364)	(4.636)
	convicted	-19.500*	0.534	-10.187*	-3.832	4.142	-13.117***
		(11.030)	(5.866)	(5.626)	(3.883)	(9.515)	(4.620)
Gambling	reported	-7.419	-0.327	-1.383	-1.221	-3.391	-1.598
		(5.017)	(3.482)	(2.366)	(1.837)	(3.520)	(2.997)
	convicted	2.373	1.660	2.402**	2.283**	3.314	3.149**
		(2.519)	(1.821)	(1.205)	(1.070)	(2.133)	(1.603)
Pornography	reported	-0.160***	0.075	-0.105***	0.014	-0.051	0.009
		(0.059)	(0.094)	(0.040)	(0.039)	(0.104)	(0.013)
	convicted	-0.162***	0.081	-0.104**	0.016	-0.047	0.010
		(0.058)	(0.094)	(0.041)	(0.038)	(0.104)	(0.012)
Prostitution	reported	10.583*	2.281	-1.301	1.959	7.498	1.374
		(5.841)	(1.640)	(2.376)	(1.522)	(4.996)	(1.090)
	convicted	10.092*	2.304	-1.260	1.894	7.099	1.389
		(5.721)	(1.635)	(2.373)	(1.496)	(4.900)	(1.089)
Controls		Yes	Yes	Yes	Yes	Yes	Yes
Province FE		Yes	Yes	Yes	Yes	Yes	Yes
Year FE		Yes	Yes	Yes	Yes	Yes	Yes
Observations		393	443	231	605	374	462

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.

3.6 References

Alotaibi, N. B., and Mukred, M. (2022) 'Factors affecting the cyber violence behavior among Saudi youth and its relation with the suiciding: A descriptive study on university students in Riyadh city of KSA', *Technology in Society*, 68, pp. 101863.

Altindag, D. T. (2012) 'Crime and unemployment: Evidence from Europe', *International review of Law and Economics*, 32(1), pp. 145-157.

Asongu, S. *et al.* (2019) 'Crime and social media', *Information Technology People*, 32(5), pp. 1215-1233.

Becker, G. S. (1968) 'Crime and punishment: An economic approach', *Journal of political economy*, 76(2), pp. 169-217.

Bell, B., Costa, R., and Machin, S. (2022) 'Why does education reduce crime?', *Journal of political economy*, 130(3), pp. 732-765.

Bhuller, M. *et al.* (2013) 'Broadband internet: An information superhighway to sex crime?', *Review of Economic studies*, 80(4), pp. 1237-1266.

Billari, F. C., Giuntella, O., and Stella, L. (2019) 'Does broadband Internet affect fertility?', *Population studies*, 73(3), pp. 297-316.

Chakpitak, N. *et al.* (2018) 'Thailand in the era of digital economy: How does digital technology promote economic growth?', *Studies in Computational Intelligence*, 753, pp. 350-362.

da Silva, A. T. C., and Menezes, P. R. (2015) 'Depression and violent crime: is there a relationship?', *BMJ Ment Health*, 18(4), pp. 114.

Diegmann, A. (2019) 'The internet effects on sex crime offenses-Evidence from the German broadband internet expansion', *Journal of Economic Behavior Organization*, 165, pp. 82-99.

Draca, M., and Machin, S. (2015) 'Crime and economic incentives', *economics*, 7(1), pp. 389-408.

Enikolopov, R., Makarin, A., and Petrova, M. (2020) ‘Social media and protest participation: Evidence from Russia’, *Econometrica*, 88(4), pp. 1479-1514.

Freeman, R. B. (1999) *The economics of crime.* Handbook of labor economics, 3, pp. 3529-3571.

Glaeser, E. L., and Sacerdote, B. (1999) ‘Why is there more crime in cities?’, *Journal of political economy*, 107(S6), pp. S225-S258.

Hawkes, N. (2015) ‘People with depression are more likely to commit violent crime, study concludes’, *BMJ*, 350.

Hipp, J. R., and Kane, K. (2017) ‘Cities and the larger context: What explains changing levels of crime?’, *Journal of criminal justice*, 49, pp. 32-44.

Larson, J. M. *et al.* (2019) ‘Social networks and protest participation: Evidence from 130 million Twitter users’, *American Journal of Political Science*, 63(3), pp. 690-705.

LawTeacher. (2013) *Regulation and Investigation of Crime on Social Media in the UK.* Retrieved from https://www.lawteacher.net/free-law-dissertations/social-media-national-identity-9938.php?vref=1.

Livingston, S. (2013) *Africa's Information Revolution: Implications for Crime, Policing, and Citizen Security.* Washington, DC: Africa Center for Strategic Studies.

Lu, H., and Kandilov, I. T. (2021) ‘Does mobile internet use affect the subjective well-being of older Chinese adults? An instrumental variable quantile analysis’, *Journal of Happiness Studies*, pp. 1-20.

Kendall, T. (2007) *Pornography, Rape, and the Internet.* Mimeo, Clemson University.

Koops, E. J. (2010) ‘The internet and its opportunities for cybercrime’ In M. Herzog-Evans (Ed.), *Transnational Criminology Manual*, pp. 735-754. Wolf Legal Publishers (WLP).

Machin, S., and Meghir, C. (2004) ‘Crime and economic incentives’, *Journal of Human resources*, 39(4), pp. 958-979.

Mancini, F., and O'Reilly, M. (2013) 'New Technology and the Prevention of Violence and Conflict', *Stability: International Journal of Security and Development*, 2(3), pp. 55.

Moore, T., Clayton, R., and Anderson, R. (2009) 'The economics of online crime', *Journal of Economic Perspectives*, 23(3), pp. 3-20.

Müller, K., and Schwarz, C. (2021) 'Fanning the flames of hate: Social media and hate crime', *Journal of the European Economic Association*, 19(4), pp. 2131-2167.

National Statistical Office of Thailand (2023) *Crime Statistics.*

National Statistical Office of Thailand (2021) *ICT Using Survey (ICTH).*

Nie, P., Peng, X., and Luo, T. (2023) 'Internet use and fertility behavior among reproductive-age women in China', *China Economic Review*, 77, pp. 101903.

Numbeo. (2023) *Crime rate statistics.* Retrieved from https://www.numbeo.com/crime/rankings.jsp

Oksanen, A., and Keipi, T. (2013) 'Young people as victims of crime on the internet: A population-based study in Finland', *Vulnerable children and youth studies*, 8(4), pp. 298-309.

Ozkan, T., Rocque, M., and Posick, C. (2019) 'Reconsidering the Link Between Depression and Crime: A Longitudinal Assessment', *Criminal Justice and Behaviour*, 46(7), pp. 961–979.

Shepherd, J. (2004) 'What is the digital era?' In Social and *economic transformation in the digital era*, pp. 1-18. IGI Global.

Srivastava, S. (2012) 'Pessimistic side of information & communication technology: Cyber bullying and legislature laws', *International Journal of Advances in Computer Science and Technology*, 1(1), pp. 14-20.

Statcounter Global Stats. (2023) *Social media platforms.* Retrieved from https://gs.statcounter.com/social-media-stats/all/thailand

Statista. (2023) *The social media penetration rate.*

Stock, J.H., Wright, J.H. and Yogo, M. (2002) 'A survey of weak instruments and weak identification in generalized method of moments', *Journal of Business and Economic Statistics*, 20(4), pp. 518-529.

Theglobaleconomy (2023) *Internet users - Country rankings.*

United Nations, Department of Economic and Social Affairs, Population Division (2019) *World urbanization prospects: The 2018 revision (ST/ESA/SER.A/420).* New York: United Nations.

Vo, T. et al. (2020) 'Crime rate detection using social media of different crime locations and Twitter part-of-speech tagger with Brown clustering', *Journal of Intelligent & Fuzzy Systems*, 38(4), pp. 4287-4299.

Wall, D. (Ed.). (2001) *Crime and the Internet.* Oxon: Routledge.

Wall, D. S. (2015) 'The Internet as a Conduit for Criminal Activity' In *Information technology and the criminal justice system*, Pattavina, A., ed, pp. 77-98.

Wang, Y. et al. (2019) 'The relationship between social media data and crime rates in the United States', *Social media+ society*, 5(1).

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

Yildiz, R., Ocal, O., and Yildirim, E. (2013) 'The Effects of Unemployment, Income and Education on Crime: Evidence from Individual Data', *International Journal of Economic Perspectives*, 7(2).

Zhu, H., Li, Z. and Lin, W. (2023) 'The Heterogeneous Impact of Internet Use on Older People's Mental Health: An Instrumental Variable Quantile Regression Analysis', *International Journal of Public Health*, 68.

3.7 Appendix

Table A3.1: Variable definitions and summary statistics (2008–2019)

Variable	Definition	Mean	Standard deviation	Minimum	Maximum	No. of observations
Dependent Variables						
rlife	Reported crime rates per 100,000 inhabitants (offense related to life, body and sex) (people)	37.772	17.131	10.942	112.355	912
clife	Convicted crime rates per 100,000 inhabitants (offense related to life, body and sex) (people)	25.117	11.064	4.092	87.137	912
rprop	Reported crime rates per 100,000 inhabitants (offense against property) (people)	74.820	46.702	15.714	384.442	912
cprop	Convicted crime rates per 100,000 inhabitants (offense against property) (people)	42.899	25.948	6.139	275.617	912
rvic	Reported crime rates per 100,000 inhabitants (offense which government is the victim) (people)	802.179	471.663	78.574	3,909.744	912
cvic	Convicted crime rates per 100,000 inhabitants (offense which government is the victim) (people)	679.119	435.609	62.614	3,914.327	912
rrape	Reported rape crime rates per 100,000 inhabitants (people)	5.125	2.817	0.000	28.365	912
crape	Convicted rape crime rates per 100,000 inhabitants (people)	3.231	1.737	26.110	28.365	912
rfraud	Reported fraud crime rates per 100,000 inhabitants (people)	10.841	6.601	0.623	86.644	912
cfraud	Convicted fraud crime rates per 100,000 inhabitants (people)	4.718	3.518	0.000	22.884	912
rdrugs	Reported drugs crime rates per 100,000 inhabitants (people)	508.749	294.829	49.109	1,898.006	912
cdrugs	Convicted drugs crime rates per 100,000 inhabitants (people)	485.899	287.509	44.198	1,878.058	912
rgamb	Reported gambling crime rates per 100,000 inhabitants (people)	186.618	162.022	0.743	1,566.885	912
cgamb	Convicted gambling crime rates per 100,000 inhabitants (people)	89.544	76.717	0.743	528.500	912
rporn	Reported pornography crime rates per 100,000 inhabitants (people)	0.505	2.304	0.000	41.054	912
cporn	convicted pornography crime rates per 100,000 inhabitants (people)	0.496	2.298	0.000	41.054	912
rpros	Reported prostitution crime rates per 100,000 inhabitants (people)	41.085	151.293	0.000	1,699.305	912
cpros	convicted prostitution crime rates per 100,000 inhabitants (people)	40.839	149.711	0.000	1,690.183	912
Explanatory Variables						
soc	Percentage of individuals using social media (%)	21.189	19.060	0.000	76.158	912
ict	Percentage of individuals owning computers or mobile phones and accessing the internet (%)	31.748	13.753	9.730	79.006	912
speed	Percentage of individuals accessing high speed broadband (%)	25.739	15.548	1.021	76.016	912
unemp	Unemployment rate (%)	0.976	0.727	0.115	8.243	912
pov	Poverty rate (%)	14.166	11.937	0.000	74.386	912
inf	Consumer price index (%)	95.638	7.491	70.367	107.164	912
edu	Average years of schooling (year)	8.018	0.845	5.560	11.300	912
dens	Population density per km^2 (people)	237.620	472.876	19.070	3,639.823	912

Table A3.2: Effect of social media on crime in different period

		Offense related to life, body and sex		**Offense against property**		**Offense which government is the victim**	
		reported	convicted	reported	convicted	reported	convicted
Panel A 2008-2011							
2SLS IV: *soc*		-0.500	-2.718	-2.262	-2.896	-9.604	3.485
		(1.898)	(1.903)	(5.885)	(2.674)	(42.802)	(33.581)
	Rape	0.005	-0.348				
		(0.641)	(0.467)				
	Fraud			0.500	0.012		
				(2.425)	(0.664)		
	Drugs					0.582	2.894
						(31.113)	(29.659)
	Gambling					-19.019	-8.404
						(30.032)	(9.636)
	Pornography					0.097	0.141
						(1.094)	(1.092)
	Prostitution					9.777	9.821
						(11.201)	(11.152)
First stage ict_{t-1}				0.117*			
				(0.064)			
F -Statistic				22.54			
Observations		228	228	228	228	228	228
Panel B 2008-2015							
2SLS IV: *soc*		0.272	1.274***	-1.409*	0.384	6.499	5.130
		(0.290)	(0.326)	(0.746)	(0.353)	(9.090)	(8.034)
	Rape	-0.065	0.050				
		(0.080)	(0.064)				
	Fraud			0.012	0.021		
				(0.225)	(0.095)		
	Drugs					-10.156	-11.042
						(7.140)	(6.917)
	Gambling					5.768	5.338***
						(3.826)	(2.067)
	Pornography					-0.0001	0.003
						(0.088)	(0.089)
	Prostitution					10.873***	10.876***
						(3.153)	(3.152)
First stage ict_{t-1}				0.319***			
				(0.044)			
F -Statistic				30.76			
Observations		532	532	532	532	532	532
Controls		Yes	Yes	Yes	Yes	Yes	Yes
Province 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.