THESIS

THE ROLE OF INFORMATION AND COMMUNICATION TECHNOLOGY (ICT) DEVELOPMENT ON INEQUALITY IN INDONESIA

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T E S I S

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THESIS

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CHAPTER I

INTRODUCTION

1.1 Background

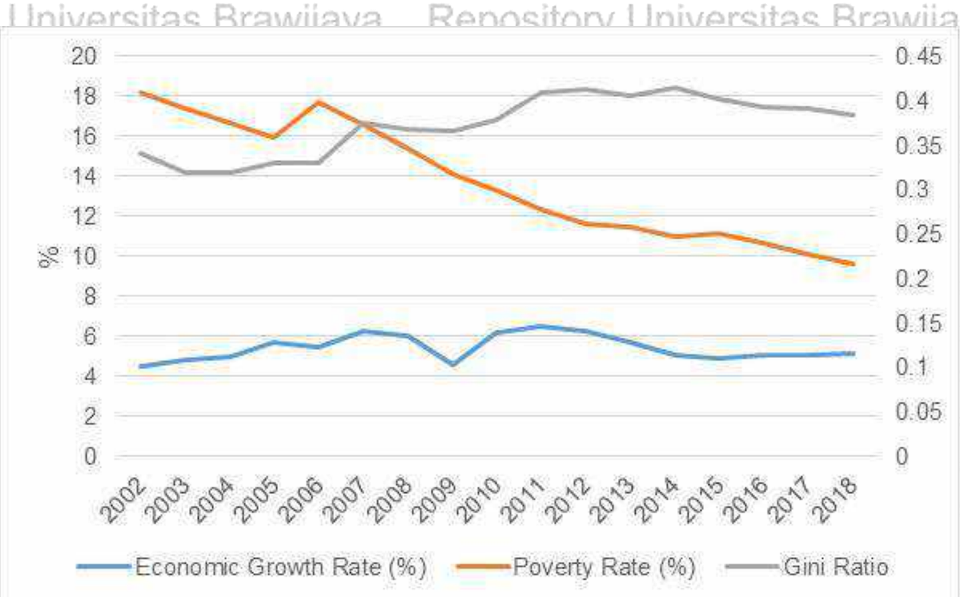
Inequality has been a center of discourse for decades due to its persistence around the world, regardless countries' income levels. According to World Inequality Report (2018), inequality has swiftly dominated North America, India, Russia, and China since 1980. It was reported that the 50% poorest of world's population has been favored with significant real income growth rates during the period. Even so, the top 1% richest of world's population managed to secure twice as much of that growth as the bottom individuals, resulting the decline of middle income groups which incorporates the bottom 90% earners in the Europe and the United States. Further, United Nations Economic and Social Commission for Asia and the Pacific (UNESCAP) has called Indonesia out on account of its high inequality contribution toward the region between 1990s and 2010s, along with China and India as the most densely populated nations. On a closer look, inequality has predominated the urban areas of China and India, whereas Indonesia's rural lives has undergone more disproportion than its urban society (UNESCAP 2018).

This urgent call was not a trivial matter for it bore damaging effect on economic and society. There has been numerous research related to the cost of inequality on economic growth and poverty alleviation. Despite economists' mixed claims[1], a series of research conducted by Berg and Ostry, from 2008 up to 2018, has relentlessly asserted that inequality indeed impede sustainable

[1] Some claimed that inequality hampers growth (Berg et al., 2018; Cingano, 2014) while others found the opposite (Forbes, 2000; Foellmi and Zweimüller, 2006), or proved that both has no relation unless certain conditions applied (Gründler and Scheuermeyer, 2018; Breunig and Majeed, 2020).

growth for it is associated with lower human capital investment, higher fertility, and weaker political institution (Berg et al. 2018), thus further intensifying the level of poverty. Nevertheless, for the past decade, Indonesia has experienced a positive and stable economic growth, a considerable decline in poverty, as well as a gradual increase of inequality – represented by Gini Ratio (Figure 1.1). Breunig & Majeed (2020) have studied cross-country regressions with respect to inequality, poverty, and their interaction and found that once poverty exceeded 30% or so, the negative effect of inequality on economic growth became significant. They suggest that although inequality has no connection toward economic growth, there are still variety of reasons on why countries consider to bring it down as it may impair social cohesion and institution.

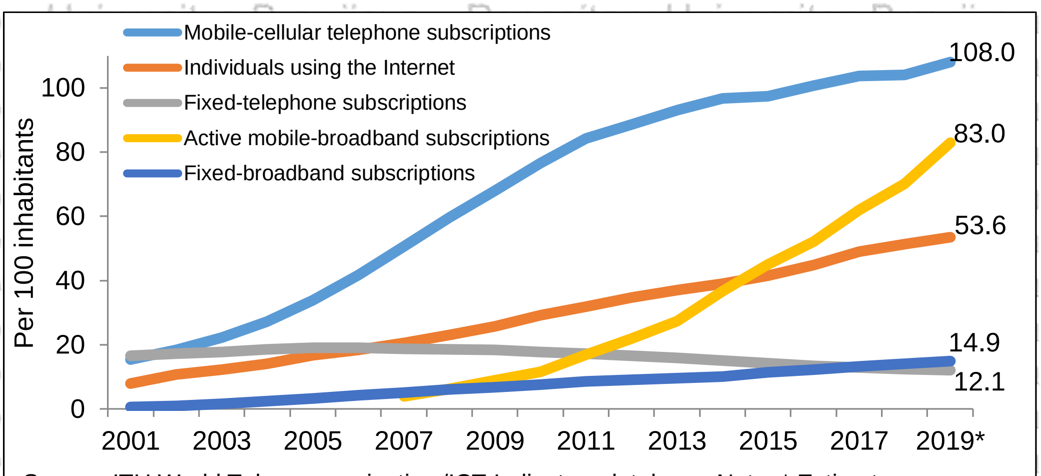
Figure 1.1 Indonesia's Economic Growth, Poverty Rate and Inequality – represented by Gini Ratio



Source: Indonesian Central Bureau of Statistics

Meanwhile, during the past decade, Information and Communication Technologies (ICTs) brought by high-speed Internet has continued to spread at unprecedented speed and scale throughout the world. The global ICT development (Figure 1.2) shows generally upward trend in the access to and use of ICTs except for fixed-telephone subscriptions, indicating a shift from fixed to mobile cellular telephony. However, fixed-broadband subscriptions continue to increase in a steadier rate compared to the mobile-broadband in consequence of the increasing growth in developing countries that is compensated by the slowing growth of developed countries as they are getting closer to saturation levels (ITU 2018), while mobile-broadband subscriptions have soared since its introduction with level of penetration in developing countries that is greater than that of developed countries, reflecting the technology's accessibility in terms of availability and affordability. Following that, the number of individuals using the internet in the less developed countries is expected to remain strong although it may approach saturation in the developed countries.

Figure 1.2 Global ICT Development

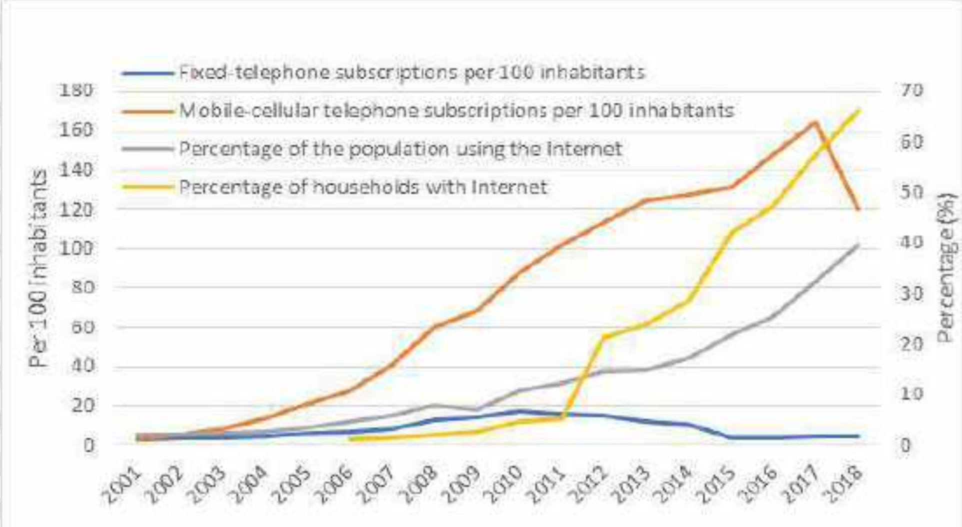


Source: ITU World Telecommunication /ICT Indicators database; Note: * Estimate

[2] Based on data published by Indonesian Central Bureau of Statistics (BPS)

In line with the trend of global ICT development, the ICT development in Indonesia is also expanding, with internet penetration rate reported to have reached 43.5 percent or over 116 million internet users as of 2019[2]. Indonesia's internet users are set to boom with the availability of inexpensive mobile telephones and expansion of mobile broadband. The strong inclination for mobile-cellular telephone has forced fixed-telephone subscriptions to experience a downturn ever since 2010, while mobile-cellular telephone subscriptions continue to rise before having a sharp decline in 2018 (Figure 1.3). The reason behind the sharp decline is a new regulation requiring all prepaid subscribers to register their phone numbers with their valid national ID and family register. Failure to comply will result in the suspension of services, resulting in the blocking of millions of prepaid SIM card holders and the corresponding drop of prepaid subscribers (Prayugo, 2018).

Figure 1.3 Indonesia's ICT Development



Source: ITU World Telecommunication /ICT Indicators database

With the emergence of technology, it certainly offers a great deal of opportunities to boost economic growth and economic development but equal distribution may not be guaranteed. On the constructive side, technology enables productivity enhancement that allows economic to accelerate (Czernich et al. 2011; Jahangard and Pourahmadi 2013) and knowledge sharing that helps society to access basic resources as well as services, thus granting more equal distribution (Sun et al. 2014). But on the other hand, it may exacerbate the existing inequality when there is lack of access due to limited infrastructure and capabilities supporting the poor (Vicente and López 2011). Kanbur, Rhee, and Zhuang (2014) have identified that technological progress, globalization, and market-oriented reform are the key drivers of rapid growth in Asia, but due to geographically uneven distribution, they can give rise to inequality. When new economic opportunities created by these drivers occur, those living in an area with access to better public infrastructure and trade zone often effortlessly seized them, generating disparity of income or consumption among regions.

In light of such dispute, it is said that Indonesia incorporates a stimulating start-up ecosystem which cover five sectors including e-commerce, online media, online transportation, travel, and digital financial services, leading to a large coming of digital economy[3]. Yet its penetration rate is considered lower than many of its peers in Asia Pacific, owing to the inadequate ICT infrastructure and uneven digital utilization among its users (McKinsey 2016). As a result, a deepening internet divide appears across socio-economic groups (Sujarwoto and Tampubolon 2016). Apart from that, a study conducted by McKinsey (2018) about online commerce in Indonesia claimed that it has

[3] Referred to article posted by Desk Editor of The Insider Stories, a privately owned blog, at October 7th, 2019 http://theinsiderstories.com/indonesia-leads-southeast-asia-internet-economy-in-2025/

helped alleviating some social issues, from job creation to social equality. Following that, they also predict that demand for online commerce will continue to soar and spread across the archipelago in the foreseeable future. By taking into consideration of the opportunities and challenges previously mentioned, it is considered relevant to address the duality impact of ICT development on inequality in Indonesia through this study.

1.2 Research Questions

Drawing upon the above explanation, this study seeks further elaboration as to whether ICT development has a role to play in the inequality in Indonesia. Instead of individual, the inequality defined here as how each region differs to one another in terms of living standards of its residents or other elements like public access to education and health services.

1.3 Research Objectives

Based on the research question, the objective of this study is to analyze whether ICT development has a role to play in the inequality in Indonesia.

1.4 Research Significance

The significance of this study is twofold, first as an empirical study that provide more insight for future studies concerning inequality across regions and ICT development in Indonesia. This study differs to the previous study in the way that it attempts to probe into ICT development as a factor of inequality in Indonesia, instead of the other way around (Sujarwoto and Tampubolon 2016). Secondly, the result of this study is expected to equip the government with a better understanding of ICT involvement in shaping inequality in the hope of avoiding serious policy implications.

CHAPTER II

REVIEW OF RELATED LITERATURE

2.1 Inequalities: Concept and Approaches

Some structural adjustments following the rise of globalization over the past decades have brought forward major changes in the role of regions within national economies (Riain 2011). Consequently, a region is considered to hold a force in economic development and regarded as the center of it, leading to the establishment of regional development studies. Meanwhile, regional development itself covers a wide range of economic issues related to exploitation of productive resources that may contribute to the welfare of a region. Not only associated with efficiency objectives that focus on the optimal use of scarce factor inputs but it also address an equity issue following a significant degree of variability in the economic development of regions.

Within regional economics, there are two prevalent classes of growth models with opposite implications in relation to inequality. One class of models follows the neoclassical growth theory which emphasizes equilibrium condition and resource allocation through market mechanism. As in the Solow's model (1956), the growth of each region moves toward a long-term 'steady state' as a result of ongoing investment, constant depreciation rate, population growth and technological progress (Gumpert 2019). Hence, the inequality is considered as a temporary disequilibrium between supply and demand, making efficient market and factor mobility to be the key of equality in long run (Wei 2015).

The temporary phenomenon is supported by Kuznets' (1955) hypothesis of inverted U-pattern on income inequality which then confirmed by Williamson (1966) in his study of regional inequality (Kim 2008). The Kuznets' hypothesis holds that income differences is likely to increase during the early stages of development and gradually decrease as the economy matures, generating the inverted U-shaped curve. Eventually, the inclination towards long-term convergence is directly addressed by Barro and Sala-i-martin (1991, 1992) through their series of works on regional convergence. They put forward two kinds of convergence: β-convergence and σ-convergence, where the former indicates that poorer regions will grow faster than richer regions while reducing the overall degree of dispersion presented by the latter (Liao and Wei 2012).

Unlike the neoclassical model where the government influence is fairly limited, another class of models may have higher reliance on government intervention following imperfect competition of market and increasing returns of scale. In these models, resources allocation through market is considered inefficient and regional development holds self-reinforcing nature, thus the gap between regions tends to persist if not widen over time (Kim 2008). Myrdal's (1957) cumulative causation mode argued that the negative backwash effect tends to reinforce the regional inequality though spread effect partially amends it, indicating the importance of policy intervention to counter the free market dominance and reduce the inequality (Wei 2015).

The cumulative causation theory was in line with the concept of growth poles formulated by Perroux (1955) and defined alternatively as a center of economic space from which growth is spread among industries through pecuniary externalities, leading to agglomeration (Meardon 2001). Later on, the new economic geography (NEG) has emerged to inquire into determinants and modeling of agglomeration or dispersion of economic activity by focusing on spatial geometry. Following the formation of core-periphery model by Krugman (1991), the spatial configuration of economic activities is, ultimately, the outcome of a complicated balance between forces that pull agglomeration (centripetal) and push away agglomeration (centrifugal).

A simple and popular measure of inequality is the decile dispersion ratio of its residents' income (expenditure), the ratio of the average income (consumption) of the richest 10 percent to the average income (consumption) of the poorest 10 percent (Haughton and Khandker 2009). Another most widely used measure is the Gini coefficient based on the Lorenz curve, which plots cumulative percentages of the population against their cumulative aggregate incomes. In addition, Kanbur and Venables (2005) have identified three possible approaches at the least when assessing spatial inequality, including unweighted variation across units, population-weighted variation across units, and variation across all individuals.

The first takes region as a unit of observation and compares its income per capita. It is "unweighted" since each region counts the same. This approach is commonly used in regional convergence analysis which addresses whether differences among regions tend to be reduced in the long-run. However, the previous approach does not measure the inequality among individuals across regions. Hence, to be able to do so, it is down to the last two approaches. The second approach considers the variation of population share across regions in measuring inequality so that the number of representative individuals from each region is proportional to its population, assuming that income distribution within a region is perfectly equal.

Instead of having representative individuals from every regions, the third approach includes the variation of individuals or households within regions by selecting a random sample to be surveyed. Thus, in this approach, the inequality reflects the actual difference of income or expenditure of individuals or households regardless of regional attributes. In addition, unlike the second approach where the within-region distribution is assumed to be perfectly equal, the inequality within region can actually be approximated using decomposable inequality measures (Milanovic 2005). Table 2.1 highlights the key differences among the three approaches.

Table 2.1 Comparison of the three approaches of inequality

	Unweighted	Population-weighted	Across all individuals
Main source of data	National/Sub-national accounts	National/Sub-national accounts	Individual/Household Surveys
Observation unit	Regions	Regions	Individual/Household
Welfare concept	Regional income per capita	Regional income per capita	Disposable income or expenditure
Within-region distribution	Ignored	Ignored	Included

2.2 ICT Development: Opportunities and Adversities

Over a couple of decades, information and communication technologies (ICT) have experienced several major developments which in turn significantly altered in the way of managing business and lifestyle. The most influential of all is the arrival of internet. Cairncross (2001) referred it as an open conduit since it is capable of transmitting anything, as long as they are on digital form like data and information, effortlessly and inexpensively. She also pointed three essential attributes out of it, including global interconnectedness, seamless convergence toward other technologies, and a key driver of digital innovation. Through these feature, internet has become an inseparable part of today's modern world.

Investment in ICT infrastructure has long been given the credit for economic growth (Datta and Agarwal 2004; Czernich et al. 2011; Atif et al. 2012; Jahangard and Pourahmadi 2013), powered by digital revolution which give rise to industrial revolution. The progressive growth is not merely about increasing productivity, but also about large contribution in raising a person's well-being through improving the way things work. Brynjolfsson and Hee Oh (2012) claimed that traditional approaches in measuring welfare gain from digital services tend to overlook the value of these innovation. A study highlighted the effect of ICT-based Market Information Services (MIS) on rural farmers has revealed that it does improve agricultural income but above all it promotes competition and resolves market failure (Katengeza et al. 2014).

The diffusion of ICT does enhance aggregate output and overall economic activities, but the distribution of income varies considerably across countries, most notably the developing countries (Yousefi 2011). To achieve equal growth, it could be through leapfrogging, by which the possibility of developing countries to catch up with the developed countries through digital technologies. However, it is only possible if those countries hold the minimum requirement, starting from having reasonably absorptive capabilities to developing virtual market in every sector (Steinmueller 2001). Eventually, Niebel (2018) called into question the leapfrogging theory for the result of his work shows a sign of detachment from its likelihood.

While the debate about its distributional effect has been deeply contested, there is clear evidence of shifts in the composition and nature of jobs available as well as wage trends (Autor and Dorn 2013; Schwellnus et al. 2018; Böhm 2017). With the rise of technology-driven economy, the contraction of labor share for capital augmentation has been predicted, leading to high number of unemployment. And as a matter of fact, such fears have proven to be overestimated (Arntz et al. 2016). Although the displacement effect on labor does not reduce the labor demand, it has reduced the labor's share in value added despite an increase in the number of employment and output as well as amount of earnings (Autor and Salomons 2018).

Besides the risk of being out of job, once technology invention brings forth automation, the structure of labor market is set to change – the so-called job polarization. The middle-skill group intensively occupying routine tasks such as manufacturing and office workers undergoes sharp fall, while at the same time both the high-skill (e.g. professionals and managers) and the low-skill (e.g. personal services) groups see significant increase (Goos et al. 2014). This job polarization in turn induces wage polarization, causing those accompanied with high-skill as well as low-skill to experience wage rise relative to those with middle-skilled jobs whose wage remains stagnant (Acemoglu and Autor 2010). At last, job polarization appears to be pervasive around the world, even in Asia-

Pacific economies (UNESCAP 2018), but wage polarization may not be unconditional (Naticchioni et al. 2014).

2.3 The Role of ICT Development on Inequality

Past studies evaluating the effect of ICT Development on regional economies have been inconclusive on whether it will further aggravate or alleviate inequality (Karlsson et al. 2010). On the one hand, some argue that ICT will help less-developed regions gaining some economic advantages on the basis of time and space exclusion of internet, providing the region with the access to better resources in order to catch up (leapfrogging theory). While others, by the same token, see the fallout of ICT in reducing inequality. They asserted that internet will fuel the economic development over the region with high level of technology absorption and access to better market, reinforcing the position of leading regions (Niebel 2018).

However, from the regional perspective of NEG theory, the distribution of economic activities are engaged in a tension between centripetal forces and centrifugal forces. The former allows a geographic concentration to take place known as agglomeration economy, whereas the latter pushes the other way by opposing the agglomeration. This kind of bifurcations model determines critical values of parameters at which the qualitative behavior of the economy's dynamic changes (Fujita et al. 1999). Changes in exogenous factors such as technology will certainly affect the balance between two forces, even generate critical points whereby any shift lead to changes in the behavior of the economy's dynamics.

The indication of agglomeration over ICT development is so evident that Tranos and Nijkamp (2013) revealed that provision of network infrastructure seems to be strongly curved by agglomeration forces. The Internet Protocol (IP) links drawn by centripetal forces had unequal distribution and marginally increased during the study period. They also claimed that regions with high level of integration toward global economy are able to secure higher level of connectivity, signifying the global-urban interdependencies. Hence, the idea that internet diffusion will eventually put an end to agglomeration economies with the emergence of digital economy needs to be reconciled with the fact that there is bias in internet distribution and it is reinforcing old patterns of agglomeration (Malecki 2002).

The main reason behind location selection of ICT industry, according to a study by Marinković et al. (2018), is human resource availability followed by political and economic environment. The availability of human resources is closely related to the region's absorptive capacity which is regarded as region's ability to make the most of incoming knowledge and information flows (Miguélez and Moreno 2015). Apart from region's ability, (Zook 2002) found that regional distribution of venture capital investment is a key driver in determining where to locate the new internet startups on the basis of local networks and knowledge for their investment which is greatly influenced by geographic proximity.

As a matter of fact, the role of internet is subjected to a certain type of knowledge which can be codified and transmitted through ICT and internet, indicating its limitation in the type of tacit knowledge. By referring to the clear distinction proposed by Polanyi (1966), between codified knowledge that can be easily passed on and tacit knowledge that is hard to transmit due to specific context and experiences, Gertler (2003) argued that geography aspects cannot be left out of tacit knowledge because of its context-specific nature. Therefore, localities and geographical proximity remain significant in regional economic development.

2.4 Previous Studies

There has been a substantial body of literature covering ICT Development impact on the regional dynamics and development over the past decades. In search of empirical evidence connecting between ICT and income inequality, a cross-national research was conducted by Richmond and Triplett (2017) and the result suggested that the impact of ICT on income inequality differs by ICT type and is highly dependent on other economic and political characteristics. They found that fixed-broadband subscriptions has inequality-increasing effect that is larger than the inequality-reducing effect of mobile subscriptions, yet this is not the case within the lowest-income countries. In their cases, ICT does not even hold any effect on the income distribution because of limited access to technology used.

In the wake of rising internet prominence, researchers have been focusing more on its role within regional dynamics. Taking into account globalization and tax policy, Ningsih and Choi (2018) studied the internet penetration effect on income inequality among Southeast Asian nations and concluded that technological change, represented by the number of internet users, has significantly reduced income inequality measured by Gini Index. Whereas, Houngbonon and Liang (2017) looked into the effects of fixed broadband internet on income inequality in France and found that it does lowers income inequality particularly once the adoption rate reaches 30% of its population, but widens the income disparities between towns.

Eventually, a more recent study by Kocsis (2020) highlighted the user acceptance as a key driver in reducing inequality regarding internet infrastructure. He argued that if one could not find any reasonable advantage of using internet, it is highly unlikely that he/she would embrace the technology due to lack of knowledge or instruments. The relevant of knowledge level in making amends on inequality is also acknowledged by Zhang et al. (2020). Employing China Family Panel Studies (CFPS), they found that regions with higher level of education experience fewer increasing inequality or the so-called buffering effect, caused by the internet.

In relation to regional growth and convergence, Sahoo (2012) explored the reasons behind the growing regional inequality across major Indian States and found that the higher level of ICT contributes significantly to the States' growth while at the same time worsen inequality across States. Additionally, by considering spatial spillovers of neighboring regions, Lin et al. (2017) detected that internet dispersion is positively correlated with economic growth, especially in developed regions, but this may lead to the divergence of regional economies, indicating the growing regional disparities. However, Celbis and Combrugghe (2014) claimed that internet infrastructure has contributed to regional convergence despite the significant spatial clustering of Turkish economic geography.

Unlike the previously mentioned research, Kim (2012) scrutinize two versions of Kuznets curve depicting how technology-inequality relationship changes with the level of technological development. The first is an inversed U-shaped curve which is based on the role of technology as the engine of growth, whereas the second is a U-shaped curve that is based on theory of innovation by Schumpeterian. The cross-national study supported the second version where inequality initially goes down before rising with technological advancement once it reaches a certain threshold. The U-shaped curve is also found in the works of Gravina and Lanzafame (2019). Table 2.2 summarizes previous studies highlighting the contribution of ICT development on the inequality.

Table 2.2 Previous studies highlighting the contribution of ICT development on the inequality

Author	Method	ICT measure	Inequality measure	Result
Kim (2012)	OLS using random-effects model	Patent and other technological indicators	Household Income Inequality	The U-shaped version of Kuznets curve is found
Sahoo (2012)	Panel fully modified OLS as well as dynamic OLS	Tele-density of the states indicating the importance of ICT sector	Gross State Domestic Product (GSDP)	The higher level of ICT contributes to the States' growth while at the same time inequality was aggravated across States
Celbis & Crombrugghe (2014)	SAR, SEM, and GSM	Density of asymmetric digital subscriber lines (ADSLs)	Regional per-capita income convergence	Internet infrastructure can reduce the time needed for regions to converge to their steady-states
Richmond & Triplett (2017)	OLS using fixed-effects model	Internet user; Fixed broadband subscription; Mobile phone subscription	Net Gini and Market Gini	The inequality-increasing effect of fixed broadband is larger than the inequality-reducing effect of mobile technology
Houngbonon & Liang (2017)	OLS using fixed-effects model	Broadband penetration rate and median broadband speed (Mbps) in town	Income at decile for a certain type of workers and Gini coefficient	Broadband internet lowers income inequality, particularly when the adoption rate reaches a critical mass of 30%, but widens income-gap between towns
Lin et al. (2017)	Global Moran's I; Maximum Likelihood Estimation (MLE)	Internet user represents internet penetration	Real GDP	Internet penetration is positively associated with growth, but its spillover effect may lead to the divergence of regional economies
Ningsih and Choi (2018)	OLS using fixed-effects model	Internet user represents internet penetration	Gini Index	Internet penetration as a proxy of technological change has reduced income inequality significantly
Gravina and Lanzafame (2019)	System-GMM of dynamic panel estimation	Patent applications and mobile phone subscription	Growth of net gini and market gini	Nonlinearities in the relationship between growth of inequality and technological progress characterized by U-shaped curve
Kocsis (2020)	OLS of cross-nation data	IT usage characteristic rates	Net income Gini	Mixed results regarding Internet diffusion and its relationship with income inequality
Zhang et al. (2020)	2SLS using fixed-effects model	Number of households with internet connections	Gini coefficient	The positive impact of internet on inequality is buffered by regional demographics and penetration level

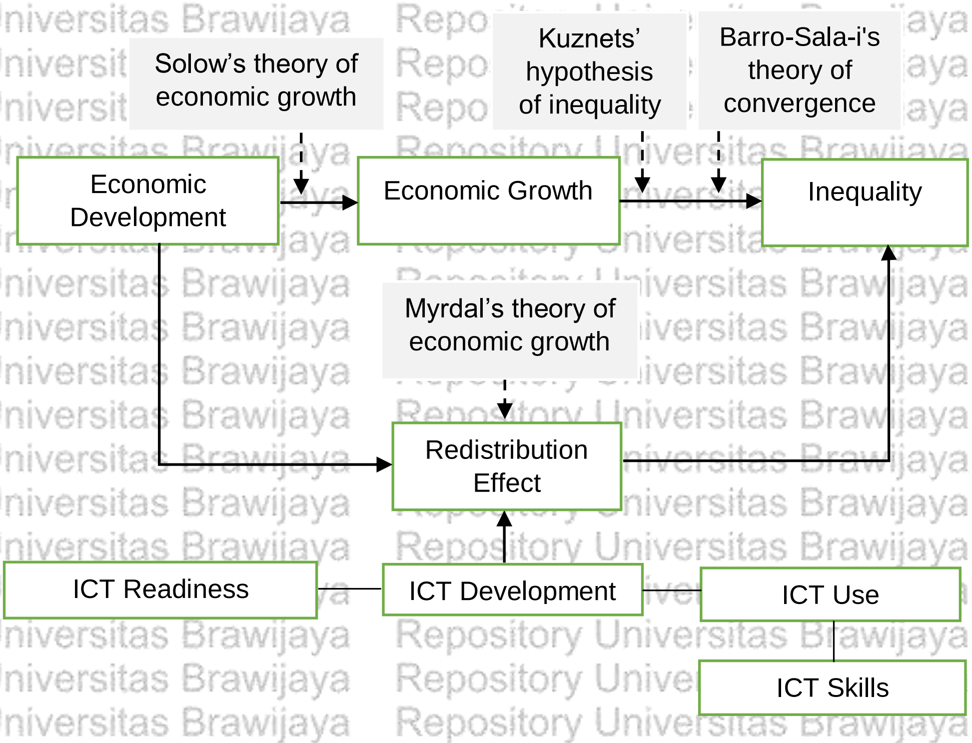
CHAPTER III

RESEARCH FRAMEWORK

3.1 Framework

To have a better understanding over an empirical study, an analytical framework is developed through a flowchart conveying the path followed by this study and its theoretical constructs. There are several theories underlying economic development and growth as an impact of ICT development, including neoclassical growth models by Solow, Kuznet's inverted-U hypothesis, convergence theory proposed by Barro-Sala-i, and Myrdal's cumulative causation theory. Some were considered to complement each other, while the other has offered a slightly different point of view indicating the complexity and dynamics of income redistribution.

Figure 3.1 Analytical Framework



The basic of Solow's model (1956) regards technology as an exogenous part of growth process, independent of capital and labor (Tranos 2012). Thus, making it possible to estimate the role of ICT development (e.g. investment in ICT) on total factor productivity of a region. And following the Kuznets hypothesis, the launch of a new technology as internet would at first raise inequality since only a small segment of the economy utilizing it would be benefitted. With the process of technology diffusion, the initial advantage will be subsequently eliminated, hence reducing the gap. This is considered as a common trend representing structural change in both advanced and developing countries (Aizenman et al. 2012).

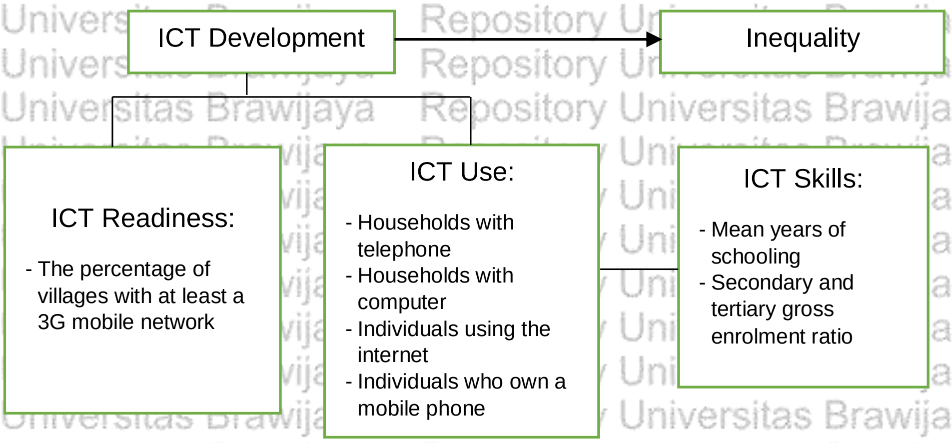
Considering the set of assumptions of a neoclassical production function combined with a constant-saving-rate rule, Barro and Sala-i-martin (2004) claimed that this model would lead to a conditional convergence. It posits that the lower the starting level of income relative to the long-run or equilibrium position, the faster the growth rate of a region, deriving from the assumption of diminishing returns to capital. The convergence is conditional because the steady-state levels of capital and output per worker depend on the saving-rate, population growth rate, and the level of production function. Consequently, technological progress is a key driver for the economy to have a sustainable growth.

Provided that opened-economy model is more relevant than the closed one, the rate of convergence tends to be higher if technological advance is passed on from developed to less-developed regions. However, differences in levels of technology may implicate the human or capital mobility, causing them to move from less-developed to developed regions and thus creating a force toward divergence. The implication is referred as "backwash effects" by Myrdal (1957). Against the backwash effect, there are "spread effects" which emerge as counteractive forces originated from economic expansion within the lower economic regions. And Myrdal argued that the outcome of these two opposite forces determined solely by market tends to sustain the inequality.

To Myrdal and other unorthodox fellows, since there are too many non-economic factors or variables to consider, thus there is no way that economic processes would be as ideal as how the neoclassical would assume. The uneven redistribution of development due to certain bias is one of instances that is being overlooked by neoclassical economists. The NEG field has attempted to fill the void by creating a general equilibrium framework under imperfect competition (Ottaviano and Thisse 2004). And even though the equilibrium is very different from the classical one, it is a steady-state position in which agglomeration or concentration is bound to rise following cumulative processes, indicating increasing returns to scale.

To account for the level of ICT development in a region, the International Telecommunication Union (ITU) has identified two key elements, the access to ICT infrastructures (ICT readiness) and the level of ICT use within the society. The latter is mainly supported by the ICT-related skills or capacities. Availability of ICT infrastructure and access to it are prerequisites for further use, while ICT-related knowledge and expertise are necessary for maximum utilization. By controlling certain variables, the study will assess the impact of ICT development on inequality. Finally, a conceptual framework can be drawn depicting research variables employed and their relations as follows:

Figure 3.2 Conceptual Framework



3.2 Hypothesis

In the light of related theories and previous research, forecasts can be deduced in the beginning for they will be verified throughout this study. The proposed hypothesis will be as follows:

1. ICT Development is significantly correlated with inequality in Indonesia
   a. ICT readiness has significant and negative correlation with inequality
   b. ICT use has significant and positive correlation with inequality at diminishing rate
   c. ICT skills has significant and positive correlation with the use of ICT

CHAPTER IV

RESEARCH METHOD

4.1 Research Approach

This study employs a quantitative approach that emphasizes on the results data processing through statistical analysis technics in order to gather new facts to prove theories. Following Leedy & Ormrod (2001), Williams (2007) stated that a quantitative research is in search of meaning through objectivity uncovered within the collected data in support of or refute of alternative knowledge claims. With regard to the purpose of this study, the approach is considered effective to infer the contribution of ICT development on inequality.

4.2 Research Time and Place

The study will be conducted in all regions of Indonesia covering all of 514 districts/cities in Indonesia. Meanwhile, variables showing ICT development of regions as well as general entropy indices portraying the level of inequality within region will resort to recent data, the 2018 data.

4.3 Data Source

The data applied in this study are secondary data mainly published by Indonesian Central Bureau of Statistics (BPS). The data varies from regional data such as Gross Regional Domestic Product (GRDP) per capita to both individual and household data directly extracted from National Socio-economic Survey (Susenas). Other than Susenas, this study also employ Indonesian Village Potential Census (Podes) from BPS which provides information of ICT infrastructure distribution, among others, across districts. Based on the collected data of Podes 2018, there are 83,931 and 514 levels of administrative government which belong to village and district/city, respectively. Apart from BPS, this study also utilize the Inclusive Economic Development (IED) index of 2018 which is annually published by National Development Planning Agency (BAPPENAS).

4.4 Operational Definitions and Measurement of Research Variables

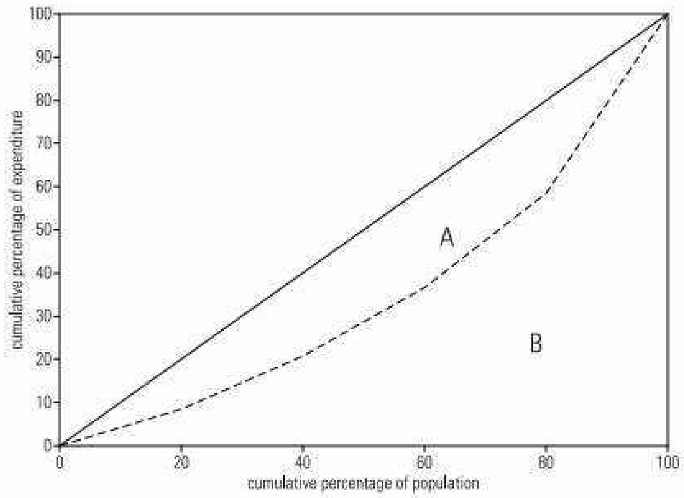
Determining the operational definition and measurement of variables used in the study is considered vital so as to have the same perception and minimize the difference in understanding them.

1. Inequality Concept

   Instead of individual, the inequality defined here as how regions differ to one another in terms of living standards of its residents or other elements like public access to education and health services. Following Haughton and Khandker (2009), Gini coefficient is regarded as good measures of inequality and among the commonly utilized ones. It is derived from the Lorenz curve that represent the distribution of a specific variable as income (or expenditure) by linking the total amount of income (or expenditure) to the number of population.

   The Lorenz curve contains not only the convex curve but also a diagonal line showing equally-distributed share of income (or expenditure) as illustrated in Figure 4.1. The Gini coeffient is defined as $A/(A+B)$, where A and B are the areas shown in the figure. The coefficient value ranges from 0 to 1 which mean perfect equality (when A is 0) and complete inequality (when B is 0), respectively. The Gini coefficient is calculated using $Gini = 1 - \sum_{i=1}^{N}(x_i - x_{i-1})(y_i - y_{i-1})$, where x_i is a certain horizontal locus while y_i is a specific vertical locus. When N equals the horizontal axis intervals, the previous equation can be simplified to: $Gini = 1 - \frac{1}{N}\sum_{i=1}^{N}(y_i - y_{i-1})$. The measure is considered as a good measure because it satisfies the minimum requirements including: symmetry, mean independence, population size independence, and Pigou-Dalton transfer sensitivity.

Figure 4.1 Lorenz curve



Source: Haughton and Khandker (2009)

Other than Gini, the IED index published by Bappenas, serves as a robustness check. The index consists of three pillars: the economic growth and development; income equality and poverty reduction; expansion over access and opportunities. The second one is particularly constructed to address inequality in terms of income, gender, and areas as well as poverty alleviation. The scale runs from 1 to 10, with 1 being the least satisfactory and 10 being the most satisfactory.

2. ICT Development Concept

Based on a conceptual framework developed by ITU (2009), ICT can be critical to the development of nations/regions that are gradually moving towards knowledge-based societies. To account for the extent of ICT development in a region, the ICT readiness and the level of ICT use within the society are the key components. The latter is mainly supported by the ICT-related skills or capacities.

a. ICT readiness

It indicates availability of ICT infrastructure and access to basic ICTs by individuals. The variable represents the percentage of villages covered by at least 3G mobile network within a district/city, excluding those only served by EDGE, GPRS or CDMA 1xRTT.

b. ICT use

The ICT use is an index composed from several indicators to portray the actual use of the ICTs. Principal Component Analysis (PCA) is used to create the index, which allows several original measures to be reconstructed with a few components that summarize as much information as possible. The forming variables are as follows:

1) Percentage of households with telephone

The telephone includes both fixed and mobile telephone, with the former refers to a telephone line with a dedicated port on a telephone exchange that connects a customer's terminal equipment to the public switched telephone network (PSTN), while the latter refers to a mobile telephone that is subscribed to a public mobile telephone service that provides access to the PSTN via cellular technology and covers both postpaid and prepaid accounts.

2) Percentage of households with computer

The computer, in this case, does not only refer to a desktop computer that usually remains fixed in one place but also a portable one (laptop) which includes notebooks and netbooks.

3) Percentage of individuals using the internet

The individuals refer to anyone using internet within the last three months from any location via fixed or mobile network, irrespective whether they have skills to log in and log out the internet or they merely resume what others left. Regardless of the device used, the internet provides access to a variety of communication services such as the World Wide Web and carries e-mail, news, and files.

4) Percentage of individuals who own mobile cellular phone

The individual owning a mobile cellular phone refers to a person who has a portable cellular phone device and one active SIM card, at minimum, for personal use within the last three months.

c. ICT skills

The ICT skill is also an index formed by PCA representing the ability and capacity to operate ICTs effectively. Unfortunately, indicators capturing such skills are currently unavailable. Hence, the level of education and literacy can be considered as a good proxy especially in developing countries such as Indonesia in which education level can be a major barrier. And with the inclusion of ICT in school curricula, attending school means higher chance for students' exposure to ICTs. Thus, the forming variables of ICT skills are mean years of schooling, secondary as well as tertiary gross enrolment ratios. Mean years of schooling presents the average number of years spent by the population aged 25 years and older in undergoing formal education, irrespective whether some of them had to repeat years during their time of study. Meanwhile, the gross enrolment ratios of both secondary and tertiary exhibit the number of students enrolled in secondary and tertiary education respectively, regardless of age, in comparison to the school-age population with the same level of education.

3. Control Variables Concept

Aside from ICT development as variable of interest in this study, relevant variables that may influence the result should be controlled. Therefore, this study includes the inter-regional recent migration and trade openness to account for the level of mobile labor, goods, and services in a region since regional economies are considered much more open than national economies due to the minimum barrier to trade including tariff, distance, socio-culture, and legal or political considerations. Another control variables, including population, population density, and GRDP per capita, are added, accounting for social and economic structure of each districts/cities. As the original data of those variables are highly skewed and heavily tailed, it is necessary to transform the variables into a natural logarithm in order that data to be close enough to a normal distribution.

All variables used in the study will be summarized in the following table:

Table 4.1 List of Research Variables

Variable(s)	Definition	Data Source
- **Response Variables**		
Gini Index	Overall inequality of household expenditures at district/city level	*Susenas* 2018
Inclusive Economic Development Index: 2nd pillar	Overall index in relation to inequality of income, gender, and areas as well as poverty alleviation	Bappenas
- **Explanatory Variables**		
ICT Readiness	Percentage of villages covered by at least 3G mobile network within a district/city	*Podes* 2018
ICT Use	Overall index composed from several indicators portraying the actual use of the ICTs within a district/city	*Susenas* 2018
ICT Skill	Overall index composed from several indicators capturing the level of education within a district/city	*Susenas* 2018
- **Control Variables**		
Recent Migrant	Ratio of migrants who lived in another districts/cities before moving into the current districts/cities within five years range prior to the survey	*Susenas* 2018
Trade Openness	Trade volume of both export and import as a share of GRDP	BPS
Population (Ln)	The natural logarithm of total population living in a district/city	BPS
Population Density (Ln)	The natural logarithm of total population living in a district/city divided by land area in square kilometers	BPS
GRDP per Capita (Ln)	The natural logarithm of total GRDP in a district/city divided by its population	BPS

4.5 Analytical Method

To assess the impact of ICT development on inequality thoroughly, the study incorporates several model specifications covering both linear and non-linear specifications. And both are estimated not only using Ordinary Least Squares (OLS) but also Two-Stage Least Squares (2SLS). The latter is particularly employed to deal with endogeneity problem. It is known that OLS reckons on minimizing residuals as small as possible to derive the best model out of various estimators. Even so, the estimation is bias if one of its explanatory variables is suspected to be endogenous due to the violation of Gauss-Markov assumptions, in which the error distribution cannot be considered independent of its explanatory variables. Hence, this study also use the 2SLS estimation, causing instrumental variables (IV) to come into play.

The model specifications are as follows:

a. Linear Model estimated by OLS

$$Gini_i = \beta_0 + \beta_1 ICT\ Readiness_i + \beta_2 ICT\ Use_i + \beta_3 ICT\ Skill_i + \beta_4 Z_i + u_i$$

b. Non-linear Model estimated by OLS

$$Gini_i = \beta_0 + \beta_1 ICT\ Readiness_i + \beta_2 ICT\ Use_i + \beta_3 ICT\ Use^2{}_i + \beta_4 ICT\ Skill_i$$
$$+\beta_5 Z_i + u_i$$

c. Linear Model estimated by 2SLS

$$Gini_i = \beta_0 + \beta_1 ICT\ Readiness_i + \beta_2 ICT\ Use_i + \beta_3 Z_i + u_i \quad (1)$$
$$ICT\ Use_i = \pi_0 + \pi_1 ICT\ Skill_i + \pi_2 Ln\ Pop\ Density_i$$
$$+\pi_3 Ln\ Pop\ Density^2{}_i + \pi_4 Z_i + v_i \quad (2)$$

d. Non-linear Model estimated by 2SLS

$$Gini_i = \beta_0 + \beta_1 ICT\ Readiness_i + \beta_2 ICT\ Use_i + \beta_3 ICT\ Use^2{}_i + \beta_4 Z_i + u_i \quad (1)$$
$$ICT\ Use^*{}_i = \pi_0 + \pi_1 ICT\ Skill_i + \pi_2 ICT\ Skill^2{}_i + \pi_3 ICT\ Skill^3{}_i$$
$$+\pi_4 Ln\ Pop\ Density_i + \pi_5 Ln\ Pop\ Density^3{}_i$$
$$+\pi_6 Ln\ Pop\ Density^4{}_i + \pi_7 Z_i + v_i \quad (2)$$

Where, $Gini$ represents overall inequality of household expenditures; $ICT\ Readiness$ represents the availability of ICT infrastructure and access; $ICT\ Use$ represents the actual use of ICTs; $ICT\ Skill$ represents the capacity to operate ICTs; Z represents control variables used in this study including recent migrant, trade openness, natural log of population, natural log of population density, and natural log of GRDP per capita; u represents the error term; and the subscript i refers to the observed municipalities.

In regard to OLS estimation (models a and b), the following classical assumption tests are performed:

1. Heteroscedasticity test

   The variance of residual in OLS should be constant over the sample period, known as homoscedasticity. Otherwise it is regarded as heteroscedasticity, resulting not in unbiased estimation but no longer best linear unbiased estimators (BLUE). In other words, OLS does not provide the estimate with the smallest variance or significance test can be too high or otherwise depending on the nature of it. To check the heteroscedasticity, a visual examination can be done using residuals plotted against fitted values or against the correlated independent variables. It should follow a pattern of line. Otherwise, a more formal test should be taken. There are several number of tests, but the most widely applied are the Breusch-Pagan (BP) test and White test.

2. Multicollinearity test

   Multicollinearity can cause the individual p-values to be misleading. In addition, the confidence intervals can be very wide, even include zero, meaning that excluding (or adding) a subject can change the coefficient values and may even change their signs. The most commonly used measure for detecting multicollinearity in a model is variance inflation factors (VIF) by identifying the correlation between its explanatory variables and the strength of the correlation. The results starts at one and have no upper limit, with one means that there is no multicollinearity. However, VIFs that is greater than 5 represent critical levels of multicollinearity where the coefficients are poorly estimated and the p-values are questionable.

3. Normality test

The error term follows the normal distribution. Although it is considered optional because OLS does not require such distribution to generate unbiased estimates with minimum variance, yet satisfying this assumption offers reliable confidence and prediction intervals. By assessing a normal probability plot of residuals against the normal counterparts can reveal whether the residuals follow a normal distribution. If it follows the straight line on the graph, then they are normally distributed. Another widely applied is the Shapiro-Wilk W test for the number of observations in between 4 and 2000.

Nevertheless, since the response variable is the Gini index which has a value bound between 0 and 1, the use of common linear regression may result in fitted values that are outside of the bottom and top limits (Ferrari and Cribari-Neto 2004). Consequently, a transformation of the response variable is required, with its values assumed to be on the real line and its mean modelled as a linear predictor based on a set of exogenous variables. This kind of model is called a beta regression model. Thus, a betafit regression established by Ferrari and Cribari-Neto (2004) is applied as a robustness check for models a and b.

There are two equations involved in models c and d, a structural equation and a reduced form equation, respectively. The endogenous variables in these models are $ICT\ Use$ for linear relation and $ICT\ Use^{*}$ for non-linear relation. The latter comprises the $ICT\ Use$ and $ICT\ Use^{2}$. Simultaneously, the instrumental variables employed for the linear model are $ICT\ Skill$, natural log of population density ($Ln\ Pop\ Density$) and its squared term. And naturally the non-linear model has more instrumental variables, consisting of $ICT\ Skill$, $ICT\ Skill$ squared and cubed, as well as $Ln\ Pop\ Density$, its cubed term and to the fourth power.

To be able to deliver unbiased estimation, it is essential that an IV designed for an endogenous variable satisfy the following pre-requisites: it should not have any correlation with the residual and must be relevant or correlated with the instrumented variable. According to International Telecommunication Union (ITU), the level of ICT use is mainly supported by ICT skills or capacities since knowledge and expertise related to ICT are considered necessary for maximum utilization. Additionally, for population density, as one would expect that the reason behind the high level of ICT use in a region is partially due to the high volume of people within a region. Consequently, this study argues that both ICT skill and population density may serve as IVs for ICT use. Meanwhile, adding IVs of some squares and additional terms such as the cubed term and to the fourth power of the exogenous variables is considered as general approach in the face of non-linear model estimation (Wooldridge 2010).

Even though the first requirement is hardly to be tested, but there are several tests that can be done in order to check the relevance of both IV and model specification including underidentification test, weak instrument test, overidentifying restrictions test, and Durbin-Wu-Hausman test of endogeneity. The underidentification test is an LM test of whether the equation is identified. Whereas, the weak instrument test applied is Cragg-Donald Wald F statistic, which is subjected to a value above 10 to be considered as sufficiently strong. In addition, the over-identifying restriction test used is Sargan statistic in which the null hypothesis reveals that the instruments are valid as they are uncorrelated with the error term, and the fact that the excluded instruments are correctly removed from the estimated equation. Finally, the endogeneity test implemented is called the "difference-in-Sargan" statistic under which the null hypothesis is that the suspected endogenous variable is in fact exogenous.

In addition, a further assessment is needed to determine whether or not sample data support a hypothesis about the population from the sample drawn, called hypothesis testing. In this testing, two types of hypothesis are used, null hypothesis (H_0) and alternative hypothesis (H_1 or H_A). Typically, the former states that there is no relationship between explanatory and response variables which later will be rejected based on sufficient empirical evidence. To determine whether null hypothesis will be rejected depends on p-values and significance levels employed. How strongly the sample data contradict the null is determined by p-values, indicating the probability of relationship obtained within the sample. Meanwhile, significance level is a standard set prior to the research, the probability of rejecting a null hypothesis believed to be true. The null hypothesis is rejected and considered statistically significant when the p-values are less than the significance level.

Another way in conducting evaluation whether the regression line shows a relationship between the response and explanatory variables is through goodness of fit measure and represented by *R*-squared. Using the percentage of the dependent variable variance, it analyses the scatter of data points around the fitted regression line as follows: $R^2 = \frac{variance\ explained\ by\ model}{total\ variance}$ The values is between 0% - 100%, the smaller the discrepancies between the observed data and the fitted values, the higher the values. Although the R-squared value indicates how strong the association between the model and the dependent variable is, it does not belong to the hypothesis testing. There is F-test of overall significance which compares the model specified to the model without independent variables, known as intercept-only model. It has null hypothesis taking stance on zero difference between the two. The null hypothesis can be rejected once the p-value is less than the significance level, which can be done by comparing the p-value and significance level.

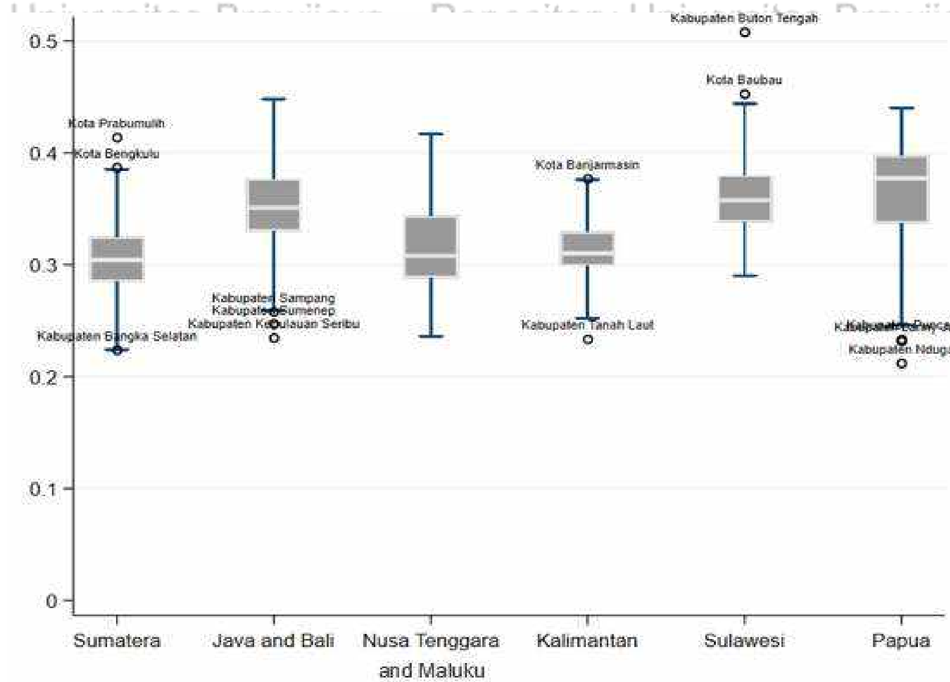
CHAPTER V

RESULTS AND DISCUSSION

5.1 Descriptive Analysis

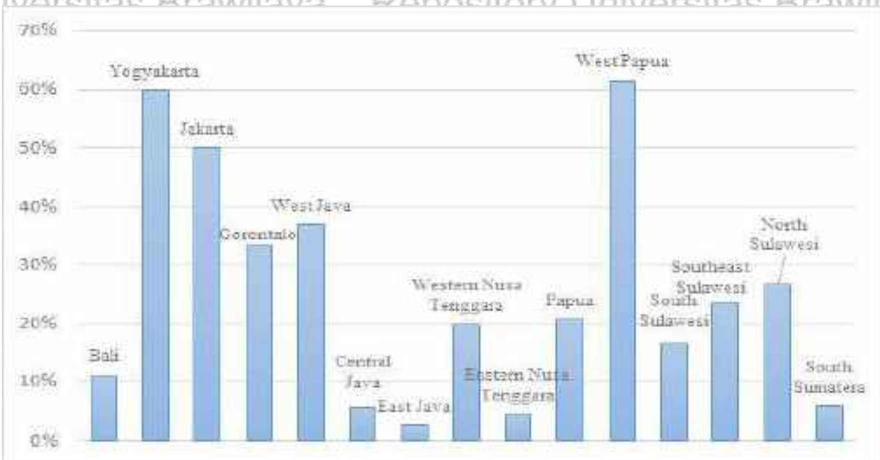
This section discusses the detail of the data set used as the main variables in the study. In 2018, the inequality as determined by Gini index is relatively similar across Indonesia (Figure 5.1). Even so districts/cities in Java, Bali, Sulawesi and Papua appear to have, on average, higher inequality than their peers in Sumatera, Nusa Tenggara, Maluku, and Kalimantan. Above all, Buton Tengah, a district in the Southeast Sulawesi, has the highest Gini up to 0.508. In fact, as Figure 5.2 indicates, the provinces with highest proportions of districts or municipalities whose Gini index more than that of National are Papua Barat, Yogyakarta, and Jakarta.

Figure 5.1 Inequality across regions in Indonesia in 2018



Source: Processed data, *Susenas* 2018

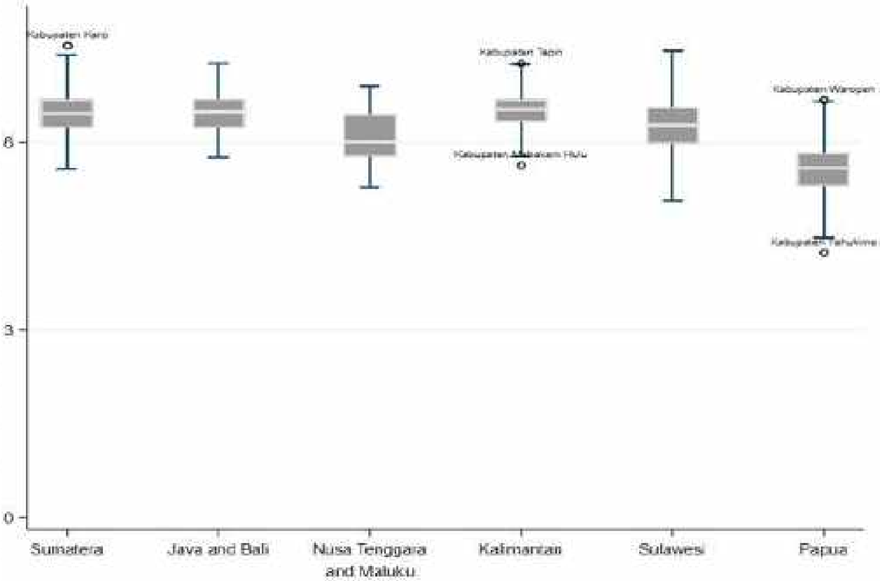
Figure 5.2 The proportion of the districts above the national value of Gini index in 2018 by province



Source: Processed data, *Susenas* 2018

On the other hand, instead of focusing only to Gini, the second pillar of IED index acts as an indicator addressing the economic development in terms of both inequality and poverty. Its measure is scaled from 1 (less satisfactory) to 10 (highly satisfactory). Thus figure 5.3 shows a different pattern from the figure 4.1, in which on average districts/cities in Kalimantan and Sumatra

Figure 5.3 The Second Pillar of IED index across Indonesia in 2018

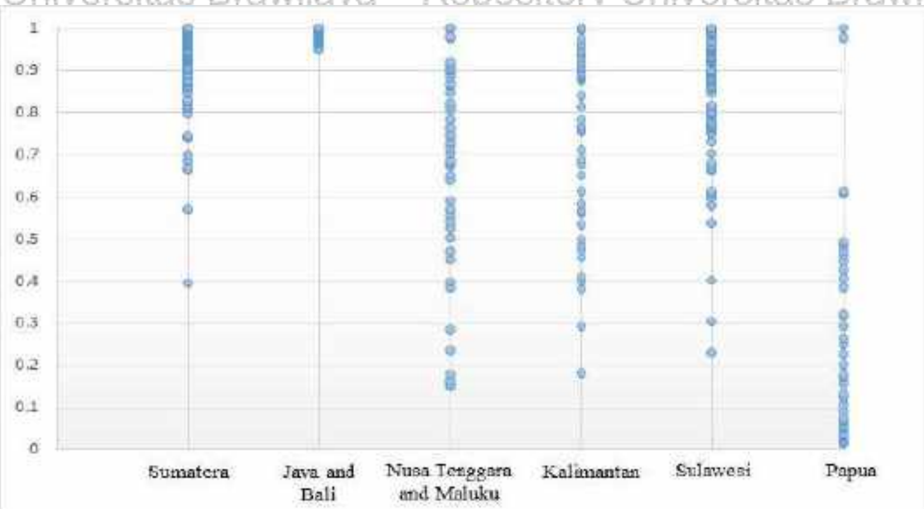


Source: Processed data, *Susenas* 2018

emerge as high-scoring regions along with those in Java and Bali. Whereas districts/cities in Papua on average barely surpass the overall National score. As a matter of fact, there are fifteen districts/cities scoring lower than that of National, and 93% of them belongs to Papua and Papua Barat provinces, underlining that these regions suffers from inequality and poverty more than other regions.

In relation to ICT readiness, which is represented by the percentage of villages covered by at least 3G mobile network within a district/city, the figure 5.4 portrays its regional dispositions in 2018. The figure indicates that infrastructure delivering network service is still unavailable in many districts/cities, especially those outside Java and Bali. This shortfall is particularly apparent to the Papua region since its districts/cities whose villages covered by the mobile network lower than 50 percent reaches 90 percent.

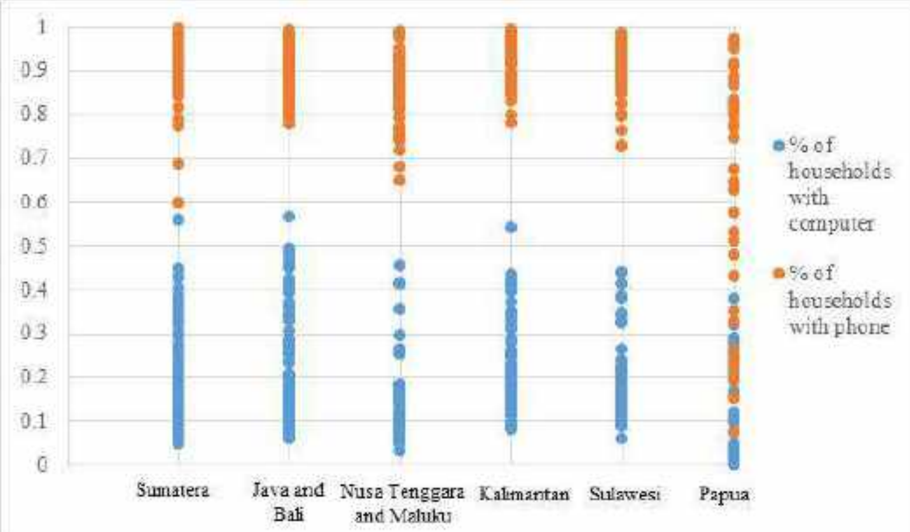
Figure 5.4 ICT Readiness across Indonesia in 2018



Source: Processed data, *Susenas* 2018

For the ICT use, as previously discussed, it covers several determinants including percentage of households with telephone (both fixed and mobile telephone), percentage of households with computer (either fixed in one place or a portable one), percentage of individuals using the internet within the last three months from any location via fixed or mobile network, and percentage of individuals who own mobile cellular phone. Apparently, the use of ICT within households is in favor of phone as the percentage of households with telephone exceeded that of households with computer (figure 5.5).

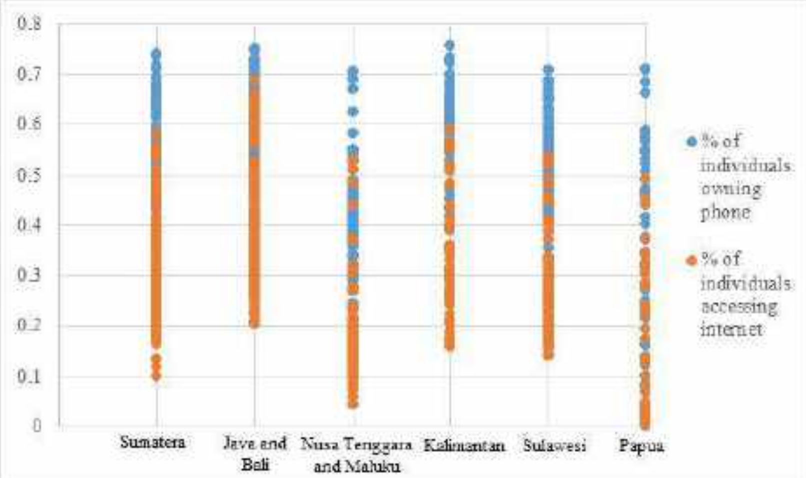
Figure 5.5 Percentage of households with computer and telephone across Indonesia in 2018



Source: Processed data, *Susenas* 2018

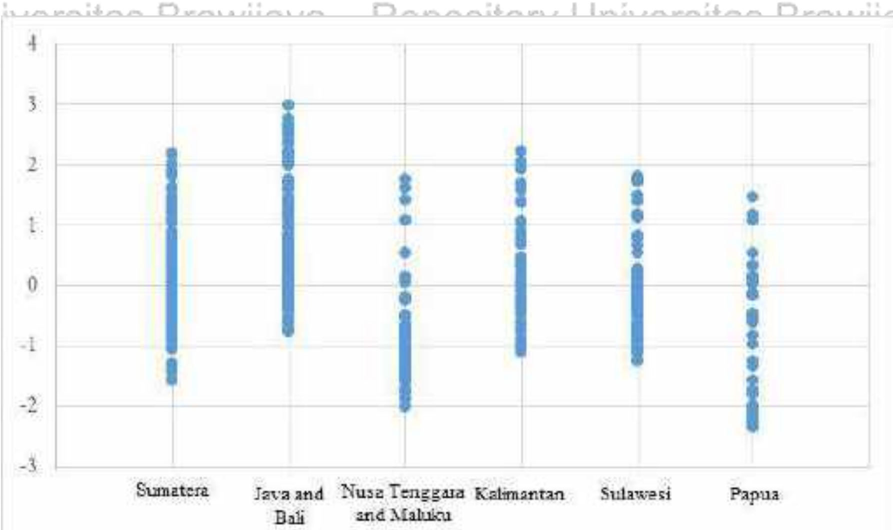
Further, as figure 5.6 indicates, percentage of individuals owning mobile cellular phone and using the internet vary among districts in each region, yet both patterns, by comparison, are similar to a great extent within every region. Subsequently, ICT use index is obtained through PCA and its value varies from minus 2.4 to positive 3. And it can be seen from figure 5.7 that most districts/cities in Java and Bali acquire positive score compared to their peers in other regions, revealing the large gap on diffusion rate of ICT use.

Figure 5.6 Percentage of individuals owning mobile cellular phone and using the internet across Indonesia in 2018



Source: Processed data, *Susenas* 2018

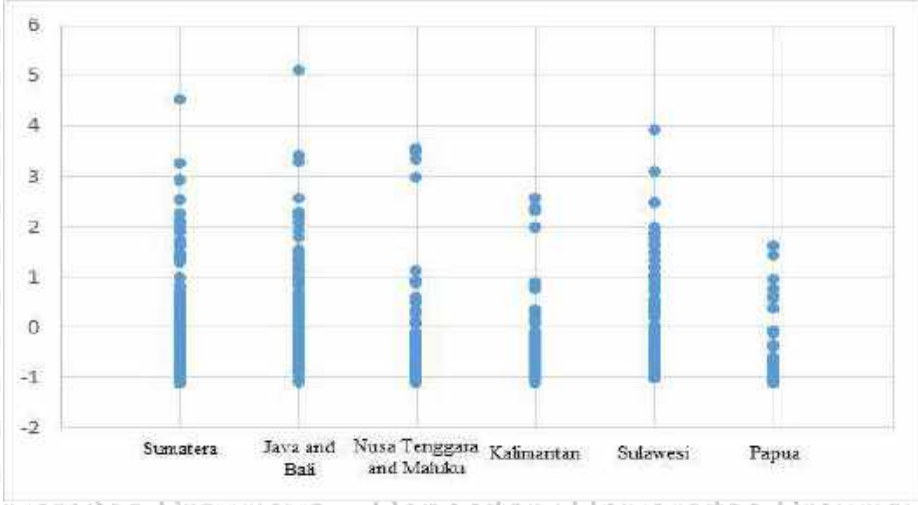
Figure 5.7 ICT Use across Indonesia in 2018



Source: Processed data, *Susenas* 2018

As discussed in the previous chapter, the ICT skill index is also formed through PCA by taking in indicators related to level of education instead of ability to use ICT-related device. Considering the average years of school and gross enrolment of both secondary and tertiary school, its regional arrangement in 2018 (figure 5.8) suggests that only few districts/cities enjoy high level of education by scoring higher than their peers. The gap is remarkably large as the high-rank districts scored three up to four times higher than those in the low-rank districts.

Figure 5.8 ICT Skill across Indonesia in 2018



Source: Processed data, *Susenas* 2018

5.2 Empirical Results and Analysis

The following section reveals the empirical results of the previously mentioned model specifications and assesses them in regards with the research question. The empirical results of ICT development on Indonesia's inequality are presented in table 5.1, in which the first two columns (a and b) are the estimation results of OLS regression while the latter twos (c and d) are the estimation results of 2SLS regression. Besides, the inclusion of the squared form of ICT use on (b) and (d) indicates the non-linear form of regression.

According to the result (table 5.1), each model is fairly equivalent by comparison. And based on the classical assumption tests, each model is efficient under homoskedasticity, has no multicollinearity problem and their residuals are close to the normal distribution. Additionally, the use of IV regression allows to look into endogeneity matter which could violate the zero conditional mean assumption, one of the Gauss-Markov assumptions. The outcome of endogeneity test shows that the p-value reject the null hypothesis, revealing that the suspect regressor(s) is indeed endogenous.

Table 5.1 The Empirical Results of ICT Development on Indonesia's Inequality

VARIABLES	(a) Gini	(b) Gini	(c) Gini	(d) Gini
ICT Readiness	-0.0595***	-0.0805***	-0.0689***	-0.117***
	(0.0108)	(0.0135)	(0.0111)	(0.0214)
ICT Use	0.0181***	0.0187***	0.0304***	0.0469***
	(0.00432)	(0.00430)	(0.00377)	(0.00724)
ICT Use Squared		-0.00439**		-0.00854***
		(0.00171)		(0.00329)
ICT Skill	0.00226	0.00374		
	(0.00266)	(0.00271)		
Recent Migrant	0.221***	0.241***	0.153*	0.114
	(0.0794)	(0.0794)	(0.0811)	(0.0847)
Trade Openness	-0.0124***	-0.0118***	-0.0132***	-0.0132***
	(0.00322)	(0.00321)	(0.00320)	(0.00330)
Ln Population	0.00518**	0.00506**	0.00441*	0.00409*
	(0.00242)	(0.00241)	(0.00238)	(0.00245)
Ln Population Density	0.00242	0.00457**		
	(0.00180)	(0.00198)		
Ln GRDP per capita	-0.00806**	-0.00810**	-0.0154***	-0.0245***
	(0.00389)	(0.00387)	(0.00387)	(0.00522)
Constant	0.374***	0.384***	0.492***	0.647***
	(0.0573)	(0.0571)	(0.0623)	(0.0857)
Observations	514	514	514	514
F-test	15.66***	14.80***	20.24***	17.66***
R-squared	0.199	0.209	0.185	0.132
Heteroscedasticity	0.946	0.632	0.584	0.741
Endogeneity test			0.003	0.000

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

In regards to ICT readiness, it can be argued that it does have a role in alleviating the inequality since the coefficient sign is negative and statistically significant. By having coefficient value ranging from 0.06 to 0.12, it means that every one percent increase in the percentage of villages covered by at least

3G mobile network within a district/city contribute to the drop of inequality by 0.06 up to 0.12. In this case the lack of access towards vital resource such as ICT infrastructure can be a barrier in technology diffusion which promote regional convergence (Celbis and Combrugghe 2014).

Conversely, ICT use appears to exacerbate the inequality since the result is significant and positive towards inequality. However, its correlation come across as nonlinear as the squared form of ICT use index is significantly associated with the inequality as well. Considering that the squared term of ICT use has negative relation with inequality and coefficient value less than that of the ICT use, it can be inferred that the effect of ICT use on inequality is non-constant as the additional use of ICTs may initially worsen the inequality before gradually rectifying it.

A robustness check using the betafit regression is conducted and the result confirms that the relationship between technology and inequality is indeed non-linear. This relationship is an extension of Kuznets curve in which technology becomes the key driver of economic growth. As economy grows, so does the inequality. Naturally, those successfully embracing technology and taking part in the growth are the main beneficiary, leaving behind others and widening the wealth gap. As emerging innovations become more widely adopted, the initial benefit will fade, resulting in a narrowing of the income gap (Barro 1999). Thus, it is completely unsurprising to find an inverted curve as in the Kuznets curve emerged in this study.

As for ICT skill, instead of having direct and significant correlation with inequality, it becomes a satisfactory IV for the third and fourth model specifications along with log of population density. Based on the first regression of 2SLS (table 5.2), it has significant and positive correlation with ICT use,

Table 5.2 The first regression of 2SLS estimation – Gini index

VARIABLES	(c) ICT Use	(d) ICT Use	(d) ICT Use^2
ICT Skill	0.288***	0.307***	-0.0125
	(0.0224)	(0.0303)	(0.0683)
ICT Skill^2		0.0174	0.429***
		(0.0275)	(0.0620)
ICT Skill^3		-0.00783	-0.0603***
		(0.00631)	(0.0142)
Ln Population Density	-0.262***	-0.227***	0.625***
	(0.0569)	(0.0593)	(0.134)
Ln Population Density^2	0.0390***		
	(0.00465)		
Ln Population Density^3		0.00779***	-0.0226***
		(0.00173)	(0.00390)
Ln Population Density^4		-0.000448***	0.00239***
		(0.000142)	(0.000321)
ICT Readiness	1.194***	1.240***	-3.294***
	(0.121)	(0.122)	(0.274)
Recent Migrant	3.538***	3.549***	2.485
	(0.751)	(0.753)	(1.699)
Trade Openness	0.0835***	0.0822***	0.194***
	(0.0309)	(0.0307)	(0.0693)
Ln Population	0.0329	0.0334	0.0151
	(0.0233)	(0.0233)	(0.0525)
Ln GRDP per capita	0.463***	0.459***	-0.164**
	(0.0316)	(0.0318)	(0.0717)
Constant	-6.727***	-6.641***	2.352**
	(0.479)	(0.483)	(1.089)
Observations	514	514	514
F-test	251.97***	129.8***	123.74***
Under identification test	0.000	0.000	0.000
Weak identification test	251.97	24.40	24.21
Over identification test	0.103	0.2135	

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

whereas the squared and cubic forms of it has significant relation towards the squared form of ICT use. With coefficient value 0.3, it can be argued that one additional point in ICT skill induce the increase of ICT use by 0.3. This finding is in line with the notion that one should have basis knowledge on technology and discover the fringe benefit of utilizing it before fully adopting the technology (Kocsis 2020).

In addition, several tests concerning the relevance of IV are also performed in the first regression of 2SLS (table 5.2) as previously discussed. The underidentification test shows the p-value where the rejection of null hypothesis indicates that the model is identified. Whereas, the weak instrument identification test applied proves that IVs are sufficiently strong as the Cragg-Donald Wald F statistics shown are higher than 10. Finally, the p-value displayed in over-identifying restriction test reflects the acceptance of null hypothesis, revealing that the instruments used are valid as they are uncorrelated with the error term, and that the IVs are correctly excluded from the estimated equation.

Meanwhile, the recent migrant seems to have a significant correlation with the inequality in the OLS estimation but appears to be insignificant in the 2SLS regression. This unsettled result may need further exploration, in part because the first regression of 2SLS estimation reveals the significant relation between the recent migrant and ICT use. Alternately, migration may have a limited effect on inequality at the regional level, owing to the fact that wage differences in Indonesia have been decreased over the last two decades (Chun & Khor 2010).

On the other hand, trade openness appears to have significant and negative correlation towards inequality, indicating its contribution in alleviating the inequality. This reaffirms the notion in which the degree of openness in trade had been affecting labors across different groups of skilled workers through creating jobs as well as lowering wage inequality (Lake and Millimet 2016). Even so, a study by Agusalim and Pohan (2018) revealed that the trade exposure significantly reduce the Indonesia's income inequality in the short-run but hold insignificant effect in the long-run.

Table 5.3 The Empirical Results of ICT Development on Indonesia's Inclusive Economic Development (IED) Index

VARIABLES	(a) IED 2ndpillar	(b) IED 2ndpillar	(c) IED 2ndpillar	(d) IED 2ndpillar
ICT Readiness	0.995***	1.045***	1.079***	1.528***
	(0.109)	(0.138)	(0.111)	(0.188)
ICT Use	0.0782**	0.0768*	-0.0594**	-0.176***
	(0.0397)	(0.0402)	(0.0296)	(0.0584)
ICT Use Squared		0.0103		0.0784***
		(0.0164)		(0.0253)
ICT Skill	-0.0572**	-0.0608**		
	(0.0233)	(0.0237)		
Recent Migrant	-0.793	-0.831	0.118	-0.0702
	(0.808)	(0.813)	(0.774)	(0.867)
Trade Openness	-0.0113	-0.0127	-0.00466	-0.00483
	(0.0267)	(0.0265)	(0.0264)	(0.0278)
Ln Population	-0.0475**	-0.0474**		-0.0374*
	(0.0204)	(0.0204)		(0.0203)
Ln Population Density	-0.00732	-0.0124		
	(0.0149)	(0.0159)		
Ln GRDP per capita	0.0809***	0.0811***	0.155***	0.215***
	(0.0306)	(0.0306)	(0.0331)	(0.0406)
Constant	5.407***	5.386***	3.789***	3.190***
	(0.483)	(0.485)	(0.419)	(0.669)
Observations	508	508	508	508
F-test	26.5***	23.58***	37.13***	25.46***
R-squared	0.353	0.353	0.330	0.276
Endogeneity test			0.008	0.003

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In light of the IED index, it is relevant to assess the impact of ICT on one of its sub components as a robustness check of the preceding finding. Yet unlike gini which high score means inequality worse off, the higher the IED score the better the circumstances as inequality and poverty decline. Therefore, the ICT readiness has positive relation with the IED index, while ICT use initially holds negative correlation before gradually in favor of the index. As for the nonlinear relation, it can only be confirmed using the 2SLS estimation. This does not only confirm the previous finding but also put forward another argument in which ICTs, particularly internet connection, can help the poor in improving their living standard through increasing access to wider market and jobs available (Hidayat et al. 2021).

According to the OLS estimation, ICT skill appears to have significant and negative relation towards the IED index, meaning that the higher the ICT skill acquired is associated with increase in inequality and poverty. However, based on the first regression of 2SLS estimation (table 5.4), it holds significant and positive correlation with the ICT use, further indicating that the higher the achievement of ICT skill leads to the higher use of ICTs. Besides, the nonlinear relationship can only be seen through 2SLS where ICT skill acts as IV along with natural log of population density, proving that ICT skill is indeed an appropriate IV for ICT use. Hence, all things considered, it is more relevant for ICT skill to have direct relation with the actual use of ICT instead of the IED index.

Table 5.4 The first regression of 2SLS estimation – IED index

VARIABLES	(c) ICT Use	(d) ICT Use	(d) ICT Use^2
ICT Skill	0.301***	0.303***	0.00353
	(0.0250)	(0.0307)	(0.0661)
ICT Skill^2		0.0196	0.423***
		(0.0282)	(0.0799)
ICT Skill^3		-0.00836	-0.0591***
		(0.00629)	(0.0209)

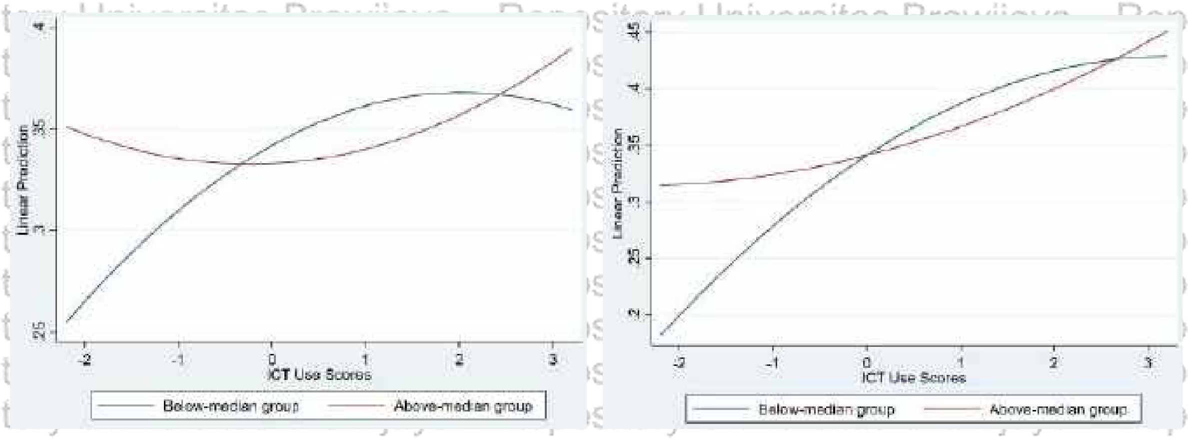
Ln Population Density	0.201***	-0.249**	0.766***
	(0.0186)	(0.108)	(0.285)
Ln Population Density[3]		0.00842***	-0.0261***
		(0.00293)	(0.00765)
Ln Population Density[4]		-0.000495**	0.00265***
		(0.000228)	(0.000598)
ICT Readiness	0.638***	1.266***	-3.455***
	(0.110)	(0.136)	(0.391)
Recent Migrant	4.563***	3.874***	2.126
	(0.828)	(0.851)	(2.155)
Trade Openness	0.0706*	0.0777**	0.198**
	(0.0417)	(0.0360)	(0.0832)
Ln Population	0.0389	0.0306	0.0296
	(0.0273)	(0.0255)	(0.0556)
Ln GRDP per capita	0.560***	0.448***	-0.143
	(0.0360)	(0.0393)	(0.0892)
Constant	-8.686***	-6.494***	1.724
	(0.428)	(0.618)	(1.535)
Observations	508	508	508
F-test	186.83***	110.7***	56.92***
Under identification test	0.000	0.000	0.000
Weak identification test	186.83	25.52	23.19
Over identification test	0.088	0.254	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

With the confirmation of the nonlinear relation of ICT use on inequality, its margin is assessed in search of variations in the role of ICT use among different level of economic development. Thus, instead of categorizing based on the spatial arrangement, it focuses on the comparison between regions whose GRDP per capita above the median value and those below-median value. The figure in 5.9 and 5.10 highlight that there is indeed different association between ICT use and inequality within the two groups. The low-income regions see the inverted U-shaped curve in which inequality increase with the additional use of ICTs before making downturn at the higher end of it. On the contrary, the higher-income regions experience the U-shaped curve as inequality slightly decline with the increasing use of ICTs only to rebound and score even higher inequality.

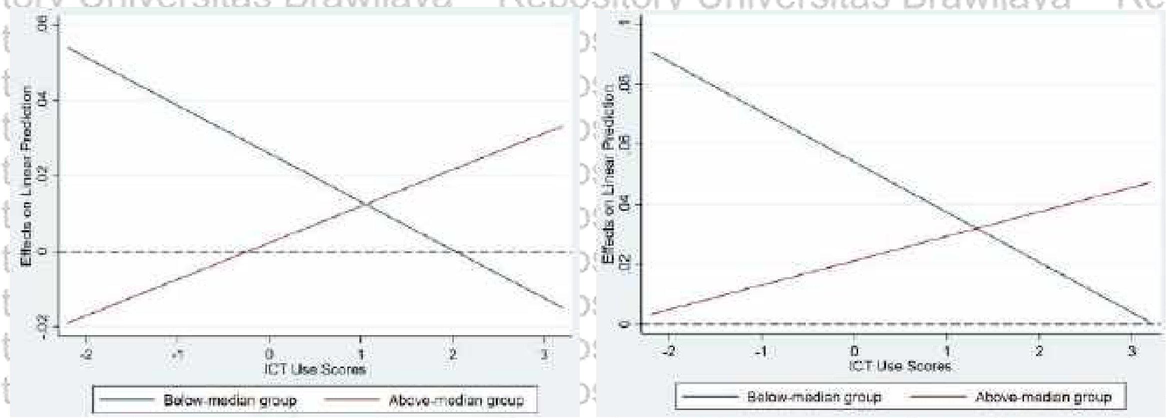
How this polarization closely related to the development stage of each region is further explained as follows:

Figure 5.9 Predictive Margins of ICT use across Groups of Municipalities



(a) OLS estimation (b) 2SLS estimation

Figure 5.10 Average Marginal Effects of ICT use across Groups of Municipalities



(a) OLS estimation (b) 2SLS estimation

a) In the lower-level of economic development, the additional use of ICT promotes not only economic growth but also inequality in the region as the economy shifts from a struggling less technologically advanced sector such as agriculture to a thriving more technologically advanced sector such as industries. Those moving to a more-advanced sector are benefited from the higher income, resulting in the widening income gap. Eventually, the inequality caused by the sectoral mobility decreases as the transition is completed.

b) For the higher-level economic development, the nature of innovation constitutes the developmental phases. In the early phase, the role of ICTs is as an equalizer because brand new products and processes are developed in result of numerous innovative initiatives by new entrepreneurs, causing barriers induced by the former innovation to be lowered or even wiped out. Albeit this ‘creative destruction’ known as Schumpeterian innovation Mark I, the later phase –known as Schumpeterian innovation Mark II, shows a strong tendency toward "creative accumulation," in which only few large firms having a significant amount of physical or human capital drive the technology innovation, thus setting high barriers for new entry and causing inequality to soar.

CHAPTER VI

CONCLUSION

6.1 Summary of Findings

By utilizing the municipal level data covering all of 514 districts/cities, this study attempted to look into the role of ICT development on inequality in Indonesia. The ICT development includes the availability of basic ICT infrastructure, the use of ICTs, and the capacity to operate it. Given the data limitation, data from 2018 is used, resulting in a cross-sectional study. The study provides both linear and non-linear models to be estimated using OLS and 2SLS, aiming for a thorough assessment.

The major findings of this study include the following matters. First, the accessibility on basic ICT infrastructure has a role in alleviating inequality, contributing to its drop up to 0.12. However, the actual use of ICTs has a non-linear relationship with inequality; at a lower level of ICT use, it gives rise to inequality before the pace of the increase slows down at a higher level of this variable, revealing a pattern similar to the Kuznets curve. Second, the ICT skill variable comprising the education level appears to have direct correlation with ICT use instead of inequality, in which an additional score on ICT skill will induce the increase of ICT use by 0.3, confirming that basis knowledge is a prerequisite for engaging in ICTs.

Third, replacing the Gini index with the inclusive economic development (IED) index as the responding variable resulted in support of previously mentioned findings. In addition, since IED index takes into account both inequality and poverty, this supports the argument that ICT may contribute in poverty alleviation by expanding access to wider market and better jobs opportunities. Finally, the association between ICT use and inequality varied across economic development levels, in which lower-income regions exhibit the inverted U-shaped curve as in the original Kuznets' curve whereas higher-income regions are subjected to the U-shaped curve, further revealing the contrasting role of ICTs on inequality across regions in Indonesia.

6.2 Policy Implications

Given that today's world is closely interrelated through ICTs, assessing the impact of ICT development on inequality in Indonesia have a number of critical implications for policymakers. First, as the availability and access to ICT infrastructure turn out to have strong and negative association with inequality, providing basic ICT infrastructure and network at a minimum throughout archipelago is indispensable, particularly towards regions outside Java and Bali. All the more since internet has become ever more prominent during the COVID-19 pandemic and digital transformation is set as one of the key objectives in the Medium-Term National Development Plan (RPJMN) 2020-2024.

Second, promoting digital inclusiveness should be the primary agenda because the inequality induced by ICTs is in part due to only a fraction of the society benefiting from it, leaving behind others who have not adopted ICTs. Clearly there are various factors impeding one to fully engage with ICTs, requiring strategic and far-reaching policies able to embrace all segments within society especially the poor and disadvantages. One of the relevant determinants identified in this study is educational attainment as regions featured with high level of education has strong and positive correlation towards the use of ICTs, hence improving education should be an integral part of digital inclusiveness policy.

Last but not least, the government's redistributive policies and spending such as cash transfer, subsidies, and other forms of social assistance, are extremely vital for relieving the inequality caused by ICTs. For regions with the inverted U-shaped curve, the policies should be directed to overcome the possible digital divide once ICTs become the driver of the economic growth. As for regions facing the U-shaped curve, the policies should be designed to prevent any conditions that may impair the fair competition in the new more-technology-advanced sector by reducing the entry barrier or enforcing rules and regulation.

6.3 Limitations of the Study

Needless to say, this study is limited to a cross-sectional study offering a snapshot of a specific point in time. Hence, to expand the current study, one might want to conduct a longitudinal study or a panel study as it allows to study changes or developments in the characteristics of the targeted population over period of time. Apart from that, the inequality applied in this study is limited to inequality within region rendering regions as separate entities. Having said that, it is highly recommended that the future study take into account the spatial effect, enabling one to assess the technological interdependence towards inter-regional inequality and further probe into the existent of regional convergence. Finally, instead of using macro data, the future study may incorporate the micro data in search of link between ICTs and inequality among individuals or certain groups.

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APPENDIX

Table 1. Summary Statistics

	Gini	IED Index	ICT Readiness	ICT Use	ICT Use^2	ICT Skill	Recent Migrant	Trade Openness	Ln Population	Ln Population Density	Ln GRDP per Capita
Observation	514	508	514	514	514	514	514	514	514	514	514
Minimum	0.212	4.240	0.013	-2.345	1.17E-07	-1.118	0.077	0.110	9.533	-0.223	8.720
The First Quartile	0.302	6.120	0.795	-0.650	0.068	-0.703	0.111	0.710	11.904	3.944	10.161
Median	0.331	6.390	0.957	-0.138	0.393	-0.287	0.126	0.980	12.514	5.004	10.504
The Third Quartile	0.361	6.660	0.996	0.559	1.210	0.391	0.144	1.424	13.369	6.755	10.896
Maximum	0.508	7.550	1	2.973	8.838	5.102	0.234	5.464	15.580	9.891	13.448
Mean	0.332	6.347	0.839	7.89E-11	0.998	2.65E-11	0.130	1.108	12.608	5.255	10.590
Standard Deviation	0.045	0.440	0.246	1	1.477	1	0.027	0.598	1.045	1.956	0.660
Skewness	0.170	-0.760	-1.865	0.383	2.141	1.662	0.947	2.057	0.096	0.130	1.021
Kurtosis	3.017	4.386	5.572	3.187	7.468	6.258	4.302	11.238	2.769	2.642	5.022

Table 2. Correlation matrix

	Gini	ICT Readiness	ICT Use	ICT Use^2	ICT Skill	Recent Migrant	Trade Openness	Ln Population	Ln Population Density	Ln GRDP per Capita
Gini	1.000									
ICT Readiness	0.008	1.000								
ICT Use	0.284	0.586	1.000							
ICT Use^2	0.170	-0.248	0.259	1.000						
ICT Skill	0.288	0.346	0.702	0.393	1.000					
Recent Migrant	0.148	-0.249	0.086	0.203	0.129	1.000				
Trade Openness	-0.111	0.049	0.220	0.065	0.069	0.119	1.000			
Ln Population	0.127	0.567	0.429	0.008	0.267	-0.399	0.020	1.000		
Ln Population Density	0.233	0.686	0.716	0.270	0.565	-0.198	0.009	0.632	1.000	
Ln GRDP per capita	0.048	0.173	0.562	0.080	0.256	0.147	0.345	0.057	0.127	1.000

	IED Index	ICT Readiness	ICT Use	ICT Use^2	ICT Skill	Recent Migrant	Trade Openness	Ln Population	Ln Population Density	Ln GRDP per Capita
IED Index	1.000									
ICT Readiness	0.557	1.000								
ICT Use	0.397	0.584	1.000							
ICT Use^2	-0.132	-0.242	0.269	1.000						
ICT Skill	0.160	0.342	0.701	0.399	1.000					
Recent Migrant	-0.111	-0.235	0.111	0.195	0.148	1.000				
Trade Openness	0.071	0.045	0.219	0.073	0.074	0.128	1.000			
Ln Population	0.247	0.564	0.424	0.019	0.254	-0.378	0.021	1.000		
Ln Population Density	0.353	0.683	0.717	0.283	0.559	-0.178	0.012	0.622	1.000	
Ln GRDP per capita	0.253	0.163	0.558	0.087	0.257	0.166	0.341	0.054	0.124	1.000

Table 3. The Results of ICT Development on Inequality across Groups of Municipalities in Indonesia

VARIABLES	(OLS) Gini	(2SLS) Gini
ICT Readiness	-0.0865***	-0.113***
	(0.0133)	(0.0230)
ICT Use	0.0258***	0.0541***
	(0.00461)	(0.00720)
ICT Use Squared	-0.00636***	-0.00836
	(0.00228)	(0.00556)
Above-median Group	-0.00896*	
	(0.00540)	
Above-median Group*ICT Use	-0.0235***	-0.0329***
	(0.00502)	(0.00593)
Above-median Group*ICT Use Squared	0.0112***	0.0124**
	(0.00307)	(0.00506)
ICT Skill	0.00323	
	(0.00266)	
Recent Migrant	0.249***	0.141*
	(0.0779)	(0.0826)
Trade Openness	-0.0113***	-0.0125***
	(0.00314)	(0.00325)
Ln Population	0.00451*	0.00446*
	(0.00236)	(0.00240)
Ln Population Density	0.00513***	
	(0.00195)	
Ln GRDP per Capita	-0.00767	-0.0273***
	(0.00468)	(0.00637)
Constant	0.392***	0.665***
	(0.0611)	(0.0964)
Observations	514	514
R-squared	0.250	0.176

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

Table 4. Marginal effects of the betafit regression for Gini index

VARIABLES	(Linear) Gini	(Non-Linear) Gini
ICT Readiness	-0.058***	-0.081***
	(0.011)	(0.013)
ICT Use	0.018***	0.019***
	(0.004)	(0.004)
ICT Use Squared		-0.005***
		(0.002)
ICT Skill	0.002	0.004
	(0.003)	(0.003)
Recent Migrant	0.215***	0.235***
	(0.079)	(0.079)
Trade Openness	-0.013***	-0.012***
	(0.003)	(0.003)
Ln Population	0.005**	0.005**
	(0.002)	(0.002)
Ln Population Density	0.002	0.004**
	(0.002)	(0.002)
Ln GRDP per capita	-0.008**	-0.008**
	(0.004)	(0.004)

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