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The Impact of Information and Communication Technologies on Income Inequality

A comparison across country income groups

Master's thesis in Management and Economics of Innovation

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Abstract

This report aims to improve the understanding of the relationship between ICTs and income inequality by examining how this impact varies across different ICTs and country income levels. The literature review presents existing studies from global and regional perspectives that assess the direct link between ICTs and income inequality. Based on the literature synthesis, two hypotheses are formulated. To test these hypotheses, a multiple linear regression model is applied to a short, unbalanced panel of data comprising 1078 observations for 120 countries from 2007 to 2017. The panel data includes the Gini index as the dependent variable and seven explanatory variables, five of which are indicators of ICT adoption. Initially, the global link between ICT and income inequality is analyzed. Subsequently, the sample is divided into low-, middle-, and high-income country subsamples to investigate how the relationship varies across income groups. By comparing the estimation results with the existing literature, the two hypotheses are confirmed, indicating that ICTs alleviate income inequality globally and across country income levels, but that there are differences in terms of which ICTs have significant impacts. The findings presented in this report may offer insights for policymakers aiming to understand how ICTs impact income inequality.

Keywords: Information and Communication Technology (ICT), income inequality, Gini index.

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1. Introduction

Information and Communication Technologies, henceforth abbreviated ICTs, have experienced rapid spread in recent years, becoming an integrated part of our daily lives and revolutionizing how we communicate and connect with one another (van Ark et al., 2011). The impact of ICTs extends beyond individuals, permeating commercial and societal aspects by eliminating information barriers, enhancing work efficiency, and fostering technological innovation in knowledge-based economies (Farooqi, 2020). These developments have resulted in reduced uncertainty and lower transaction costs, driving economic growth and transformation on a global scale (Chen, 2005). ICT investments have substantially increased in both developed and developing countries, including hardware, software, internal spending, and telecommunication investments (Bankole et al., 2011).

ICT, as a broad concept, includes a range of technologies that have shaped our society throughout history, from older ICTs like radios, mainline telephones, telegram, and television, to newer ones like mobile phones, computers, and the internet (Santos et al., 2017). Despite the absence of a standardized definition, various authors and institutions have offered their interpretations, with UNESCO describing ICT as a "diverse set of technological tools and resources used to transmit, store, create, share, or exchange information" (UNESCO, 2023). Given the spread and extensive presence of ICT in our society it has become a widely studied topic, attracting the attention from both researchers, economists, and policymakers (Aksentijević, 2021). Following the United Nation member states' adoption of the 2030 Agenda for Sustainable Development, there has been a rising interest in how ICTs can enable reaching the 17 Sustainable Development Goals (SDGs) that are encompassed by the agenda (UN, 2015). In particular, several studies have been conducted in relation to Sustainable Development Goal 10 (SDG 10), which aims to reduce inequality within and among countries (Richmond & Triplett, 2018; Canh et al., 2020; Yilmaz & Koyuncu, 2018; Lin et al., 2017). Studying income inequality is of great societal interest, and it can serve as an indication of poverty and inequalities in opportunities more widely by encompassing unequal access to education, health care and good-quality childhood nutrition (UN DESA, 2019). The importance of combating income inequality is further underlined by the circular and intergenerational relation between economic distress and mental distress which causes economic inequality to persist over generations (UNDP, 2022).

Moreover, income inequalities create digital divides that deprive parts of the population from the possibilities offered by ICTs; while the average earner of a country may afford a selection of ICTs, the poorer segment of the population perhaps does not (ITU, 2022). As shown in the research conducted by Pedrelli (2001) for the European Parliament, ICTs present prospects to combat poverty in developing countries. Specifically, ICTs have the potential to aid poor individuals in business development, education, and health where it can be used for improving countries' socioeconomic development

(Majeed & Ayub, 2018). In addition, as a pathway to reducing poverty, decreasing income inequality is more efficient than increasing GDP per capita growth; a one percent decrease of all countries' Gini coefficient, which is the most commonly adoption measure of income inequality (De Maio, 2007), has a larger impact on reducing global poverty than a corresponding increase of all countries' annual growth rate (UN DESA, 2019). Further, accomplishing a decrease of a country's Gini coefficient is argued to be less difficult than increasing a country's annual growth rate. Thus, ICTs carry significant potential in enabling the successful accomplishment of SDG 10, but the greater degree to which a country adopts ICTs, the more a lack of accessibility becomes a challenge.

Studying the two concepts in tandem is complex since there are theoretical justifications for the impact of the adoption of ICTs on income inequality to be both negative, such that increases in ICTs alleviate income inequality, and positive, such that increases in ICTs exacerbate income inequality (Richmond & Triplett, 2018). Research on the link between ICT and income inequality has been conducted on a global level, on geographical regions, and on groups of countries, reporting various results. Several proxies can be used to measure the development of ICTs, with measures of mobile, fixed broadband and internet diffusion being most prominent in studies that examine the relationship between ICT and several economic and societal concepts (Aksentijević, 2021; Appiah-Otoo & Song, 2021; Richmond & Triplett, 2018). The various findings that have resulted from the research on the link between ICT and income inequality appear to depend on two key aspects: the type of ICT studied, and the countries examined, with differences across low-, middle-, and high-income countries (Richmond & Triplett, 2018; Bauer, 2018; Canh et al., 2020; Yilmaz & Koyuncu, 2018; Lin et al., 2017). Furthermore, the level of adoption is also found to influence the total impact of ICT on income inequality, with high-income countries having a larger ICT adoption compared to low-income countries (Patria & Erumban, 2020; Billon et al., 2009). The apparent paradox between the impact of ICTs on income inequality on the global level and the country level has created a need for further research that can advance the understanding of the mechanisms with which ICTs can impact income inequality (Pepper & Garrity, 2015; Bauer, 2018).

This study aims to improve the understanding of the relationship between ICTs and income inequality by studying how the relationship differs across different ICTs, both globally and for countries with different levels of income. We fill this research gap by quantitatively studying the relationship using updated data of a large set of ICT variables from 120 countries between 2007 and 2017. By analyzing our estimation results and discussing our findings in relation to existing literature, we conclude that ICTs alleviate income inequality globally and across country income levels, but that there are differences in terms of which ICTs have significant impacts.

2. Literature Review

The literature review is structured as follows. Initially, a review of the existing literature studying the direct link between ICTs and income inequality is conducted by drawing on literature adopting both global and regional perspectives. Thereafter, we present literature that examines the indirect effect that ICTs have on income inequality through their impact on economic growth. Throughout the section, it is further highlighted that the direct and indirect impact of ICTs on income inequality differs across countries belonging to different income groups. To avoid confusion, we note here that the literature lacks consistent definitions for income groups. Terms such as developing, poor, and low-income countries often refer to the same set of countries, while developed, rich, and high-income countries similarly encompass a specific group of nations.

2.1 ICT and Income Inequality Globally

Studies that investigate the link between ICT and income inequality on a global level have led to varying conclusions, with Pepper and Garrity (2015) stating that there is an apparent paradox between the impact of ICTs on income inequality on the global level and the country level, and that more research is needed to understand the impact of ICTs on income inequality. Bauer (2018) states that the mechanisms with which ICTs affect income inequality are only partially understood, arguing that ICTs are never neutral, neither good nor bad. Richmond and Triplett (2018) state that in principle ICTs can both improve and exacerbate income inequality.

Studying 109 countries covering a 14-year period between 2001 and 2014, Richmond and Triplett (2018) find that the relationship between ICTs and income inequality varies across different ICTs and countries' level of income. On a global level, the study displays statistically significant evidence that internet and mobile usage decrease income inequality while fixed broadband usage increases income inequality. Among the three ICTs, the effect of fixed broadband is shown to be strongest with internet usage and mobile usage ranking second and third, respectively. Additionally, by creating subsamples of countries based on their level of income, the study displays that there are differences between low-, middle-, and high-income countries in terms of how ICTs affect income inequality. In low-income countries no ICTs have a significant effect, in middle-income countries mobile usage has a negative and significant effect while fixed broadband usage has a positive and significant effect, and in high-income countries only fixed broadband usage has a positive and significant effect.

In another study of the impact of ICTs on income inequality including 87 countries and covering approximately the same time period, namely 2002 to 2014, Canh et al. (2020) obtain results that are somewhat consistent with those obtained by Richmond and Triplett (2018). In accordance with Richmond and Triplett (2018), Canh et al. (2020)

find that on a global level both internet and mobile usage have statistically significant and negative relationships with income inequality. However, as opposed to Richmond and Triplett (2018), the study finds that mobile usage has a stronger effect than internet usage on income inequality. The results continue to differ between the studies when the entire sample of 87 countries is divided into subsamples of low- and high-income countries. While Richmond and Triplett (2018) find that mobile and internet usage do not have statistically significant relationships with income inequality for neither low- nor high-income countries, Canh et al. (2020) find statistically significant evidence that both internet and mobile usage decrease income inequality in both low-income and high-income countries. Additionally, the study finds that fixed telephone usage has an insignificant effect on income inequality for the entire sample as well as the two subsamples of countries.

Further, Yilmaz and Koyuncu (2018) study 182 countries between 2000 and 2013 and find statistically significant evidence that internet usage and mobile usage decrease income inequality globally and thus agree with both Richmond and Triplett (2018) and Canh et al. (2020). However, as opposed to Richmond and Triplett (2018), Yilmaz and Koyuncu (2018) find that fixed broadband usage decreases income inequality and, additionally, that the use of personal computers leads to higher income inequality. In terms of which ICT has the largest effect on income inequality, Yilmaz and Koyuncu (2018) disagrees with Richmond and Triplett (2018) by finding that fixed broadband has the weakest effect. The results also differ from those obtained by Canh et al. (2020) in the sense that internet usage has a stronger effect on income inequality than mobile usage.

Lastly, Lin et al. (2017) apply a spatial quantile regression model for two datasets, one with 114 countries for the year of 2001 and one with 115 countries for the year of 2005, and find that the effect of internet usage on income inequality on a global level is negative such that income inequality decreases as internet usage increases. These results are consistent with those obtained by both Richmond and Triplett (2018), Canh et al. (2020) and Yilmaz and Koyuncu (2018). However, the results that Lin et al. (2017) obtain for low-income countries, namely that internet usage exacerbates income inequality, do not agree with neither Richmond and Triplett (2018) nor Canh et al. (2020). For high-income countries, results obtained by Lin et al. (2017) are consistent with those obtained by Canh et al. (2020) in that internet usage decreases income inequality.

In addition to studies that discover the direct link between ICTs and income inequality, there are studies that explore how ICTs interact with other variables to affect income inequality. Santos et al. (2017) use data for 111 countries between 1960 and 2003 to study the effect of the interaction between technology and human capital on income inequality and find that increased adoption of several technologies contribute to a rise in inequality while none contribute to an inequality drop. Among the technologies that can be defined as ICTs that contribute to a rise in inequality are mobile phones, the

Internet and fixed telephones. Further, the authors construct an index of modern ICTs consisting of the adoption rates of computers, ATMs, the Internet and mobile phones and split the sample of 111 countries into subsamples of rich and poor. The results show that modern ICTs contribute to a rise in inequality for rich countries while no statistically significant relationship is found for poor countries.

Other indirect effects that have been studied for the relationship between ICT and income inequality are financialization (Daud et al., 2021) and gender inequality (Shah and Krishnan, 2023). Daud et al. (2021) study how digital technology affects the effect of financialization on income inequality. Using 54 countries between 2010 and 2015 and the number of secure internet servers per one million people as a proxy for the advancement of digital technology, Daud et al. (2021) conclude that as digital technology improves, financialization widens income inequality. Shah and Krishnan (2023) utilize data from 86 countries between 2013 and 2016 to study the relationship between ICT development, gender inequality and income inequality and find that gender inequality mediates, or in other words transmits, the effect of ICT development on income inequality in such a way that ICT development leads to lower gender inequality, which in turn leads to lower income inequality.

In a review of the existing literature Bauer (2018) states that a country's level of income is only one of many important factors that determine the effect of ICTs on income inequality and argues that the dynamic interrelations between these factors and the different mechanisms through which ICTs affect income inequality makes it impossible to clearly map how the relationship between ICTs and income inequality differ between countries with different levels of income. However, it is also concluded in the study that ICTs historically have contributed to increased income inequality in high-income countries and that ICTs present opportunities for low- and middle-income countries to alleviate poverty.

As illustrated by this section, the results obtained from studies that examine the link between ICTs and income inequality on a global level are ambiguous, not only in terms of which ICTs exhibit statistically significant relationships but also in terms of the direction of their impact. It has further been highlighted that results appear to differ across countries belonging to different income groups.

2.2 ICT and Income Inequality Regionally

In addition to the literature that studies the link between ICTs and income inequality globally, there is a range of studies that focus on specific geographical regions and groups of countries. Cioaca et al. (2020) study how the transition to a digital society impacts income inequality on a European level by utilizing panel data for 28 European Union member states between 2008 and 2018. In the study, a country's transition into the digital society is proxied by the ICT sector's share of the country's GDP and level of internet access, and both variables are shown to have statistically significant negative

relationships with income inequality. Given that nearly all European countries are classified by the World Bank as either high-income or upper-middle-income (Hamadeh et al., 2023), these results are consistent with much of the literature that compares the link between ICT and income inequality for countries of different levels of income (see e.g. Lin et al., 2017; Canh et al., 2020; Yilmaz & Koyuncu, 2018). While Cioaca et al. (2020) do not discuss how the relationship between ICTs and income inequality varies according to a country's level of income, Kharmolava et al. (2018) provide evidence that the impact of technological change on income inequality in European countries decreases the more economically developed the country is.

Moreover, in a study of 28 OECD countries, which almost exclusively consists of high-income countries, Khan et al. (2020) hypothesize that ICTs decrease income inequality while arguing that there is theoretical justification for the alternative hypothesis that ICTs can increase income inequality. Using the ICT Development Index (IDI) developed by the International Telecommunication Union (ITU) as a proxy for ICTs, it is concluded that the alleviating effects outweigh the exacerbating effects and, as such, that ICTs decrease income inequality. However, given that the study uses the IDI, it does not provide any evidence of the differential impact of different ICTs. Moreover, while the results tend to agree with existing literature on the link between ICTs and income inequality for high-income countries, the authors state that the generalizability of the results is limited since the study is based on data for a single year, namely 2016. Khan et al. (2020) further state that a study of low-income countries can be expected to yield different results because such countries exhibit different characteristics in terms of, *inter alia*, infrastructure and education levels.

In another study of middle- and high-income countries, namely G20 countries, Yin and Choi (2022) examine the effect of digitalization on income inequality by using a dataset between 2008 and 2018. Digitalization is proxied by the separate effects of internet, mobile and fixed broadband usage and thus enables an analysis of the differential impact of these different ICTs. For the entire sample of G20 countries, Yin and Choi (2022) find that internet usage is negatively correlated with income inequality while mobile and broadband usage have no significant impacts. Comparing these results to existing literature is difficult since there are no studies, to our knowledge, that examine the separate impact of different ICTs on income inequality for a combination of middle- and high-income countries. While Richmond and Triplett (2018) find that internet usage does not have a significant impact on income inequality for middle- or high-income countries, it should be noted that they do not analyze these samples of countries jointly like Yin and Choi (2022) and it is therefore not possible to conclude that the results are inconsistent between the two studies. However, the previously presented study of European member states by Cioaca et al. (2020) includes a mix of middle- and high-income countries and also concludes that the internet alleviates income inequality but does not provide a basis for comparison with regards to mobile and broadband subscriptions.

The results that Yin and Choi (2022) obtain for their respective samples of middle- and high-income countries are easier to place in the context of existing literature. For high-income countries, Yin and Choi (2022) find that internet usage as well as both mobile and fixed broadband usage increase income inequality in high-income countries. Interestingly, none of these results have been obtained in the other studies presented in this report that specifically study samples of high-income countries. For middle-income countries, Yin and Choi (2022) find that internet and broadband usage decrease income inequality while mobile is not significant. These results are inconsistent with Richmond and Triplett (2018) who find that the effect of internet usage is insignificant, that fixed broadband subscriptions increase income inequality and that mobile subscriptions decrease income inequality for middle-income countries.

While the above-mentioned studies focusing on regions or groups of countries that mainly consist of high- and upper-middle-income countries yield ambiguous results, the results are more consistent in studies that focus on low- or lower-middle-income countries. Adams and Akobeng (2021) study 46 African countries between 1984 and 2018 and find that internet, fixed broadband, and mobile usage all have direct alleviating impacts on income inequality. Asongu (2015) studies the income-redistributive effects of mobile penetration in 52 African countries and finds that an increase in mobile penetration improves income inequality through several different mechanisms including improved financial access and female empowerment. Mutiirria et al. (2020) study the impact of ICT on income inequality for 31 sub-Saharan African countries by constructing an ICT index based on internet, broadband, mobile and fixed telephone usage as well as internet bandwidth and conclude that it correlates positively with inclusive growth and alleviates income inequality by benefiting the poor more than the rich.

ICTs have also been proven to decrease income inequality in Africa through interactions with other variables. Tchamyu et al. (2019a) study how ICTs modulate the impact of education on income inequality for 48 African countries between 2004 and 2014 and conclude that internet, mobile and fixed broadband usage all contribute to a decrease in income inequality. Similarly, the role of ICTs on income inequality through financial development has shown to improve income inequality (Tchamyu et al., 2019b). Additionally, in a study of five lower-middle-income countries in South Asia between 2005 and 2019, Ahmad et al. (2022) construct an ICT index composed of internet usage, fixed broadband subscriptions, mobile cellular subscriptions and fixed telephone subscriptions and find that an effective application of ICTs reduce income inequality in South Asia through improved access to and quality of education, especially for the underprivileged.

Furthermore, Patria and Erumban (2020) and Ganjoei et al. (2021) present in their regional and local studies that the link between ICT and income inequality depends on a country's level of ICT adoption. Patria and Erumban (2020) investigate ICT adoption and its impact on income inequality in 33 Indonesian provinces in the period 2012 to

2016, using mobile phone, internet, and computer access as measures of the ICT adoption rate. It is evidenced that at low ICT adoption rates, income inequality increases until a certain point on the curve after which higher ICT adoption is argued to reduce income inequality. According to Patria and Erumban (2020), this proves an inverted U-shape relationship between ICT adoption and income inequality. They further calculate the turning point on the curve where the impact of additional ICT adoption on income inequality changes from positive to negative. For mobile phones, computers, and the Internet, this occurred at 25% average adoption ratio, while the threshold was 17% when taking only computer and internet into account.

The findings by Patria and Erumban (2020) are in line with the results of Ganjoei et al. (2021). Ganjoei et al. (2021) examine the relative usage of internet, mobile and fixed telephones in relation to the Gini coefficient in Iran from 1994 to 2018. They show that income inequality initially increases with increased ICT usage, but that the direction of the relationship eventually switches such that at higher rates of adoption, increases in the adoption rate leads to lower income inequality. Ganjoei et al. (2021) therefore conclude that the relationship between ICT and income inequality is inversely U-shaped. In similarity with Patria and Erumban (2020), Ganjoei et al. (2021) also present the threshold level for the U-shape relationship, which according to Ganjoei et al. (2021) is positioned with a lower level at 14.3 % and an upper level 32.1% for internet adoption, meaning that the effects are the strongest outside of these boundaries.

The studies that focus on geographical regions or certain groups of countries further underline the ambiguous evidence of the relationship between ICTs and income inequality, highlighting the apparent need for further studies to be conducted on the topic by comparing the varying impact of ICTs on income inequality for different income groups.

2.3 Economic Growth, ICT, and Income Inequality

Economic growth has a close relationship to ICT and income inequality in research, with the relationship between ICT and economic growth and, further, the relationship economic growth and income inequality being well addressed in literature (Chen, 2003; Vu et al., 2020). ICT has an indirect effect on income inequality via its impact on economic growth (Untari et al., 2019), a relationship that is further reinforced by Pepper and Garrity (2015) who show that ICTs affect economic growth such that they decrease poverty in developing regions. Pepper and Garrity (2015) further argue that this relationship is especially true for ICTs such as mobile phones that have spread across the developing countries, contributing to income growth by acting both as an educational tool and a communication device for sharing public and private information. Untari et al. (2019) use panel data from Indonesian provinces between 2011 and 2016 and find that ICT has a direct positive impact on economic growth and an indirect impact on income inequality through economic growth.

The literature between ICT and economic growth is rich and rapidly growing (Vu et al., 2020). Cardona et al. (2013) find that the productivity effect of ICT is both positive and significant and thus that the link between ICT and economic growth is positive. Similarly, Stanley et al. (2018) conclude that ICT technologies contribute positively to growth. A systematic literature review published by Vu et al. (2020) that reviews 208 academic papers published between 1991 and 2018 examining the causal link between ICT and economic growth finds that the literature overwhelmingly confirms the positive relationship between ICT and economic performance. The paper further argues that the time has come for the research on the ICT-growth link to shift its main focus from evidencing the positive relationship to advancing the understanding of it, for example by understanding the difference between rich and poor countries.

Results from studies that examine how the ICT-growth link differs between rich and poor are somewhat inconsistent. Papaioannou and Dimelis (2007) study 42 developed and developing countries and while they find that the ICT-growth link is positive for both sets of countries, they also find that the link between ICT and economic development is more positive for developed countries. On the other hand, Thompson and Garbacz (2011) find that low-income countries derive significantly more benefit from ICT and in a study of 123 countries between 2002 and 2017, Appiah-Otoo and Song (2021) conclude that poor countries tend to benefit more from the ICT revolution. However, Niebel (2018) finds that there are no statistically significant differences between developed, emerging, and developing countries.

The complexity of the link between ICT, economic growth and income inequality is further amplified through the different nonlinear relationships between economic growth and income inequality that have been found in existing literature. Kuznets (1955) argues that the relationship between a country's level of income and income inequality forms an inverted U-shape pattern such that income inequality initially increases as the level of income increases, but then starts to decrease as the level of income passes a certain threshold. As such, economic growth may both increase or decrease income inequality depending on the country's existing level of income. Later studies confirm this hypothesis, with Nielsen and Alderson (1997) arguing for the importance of the Kuznetian pattern. List et al. (1999), using an unbalanced panel of data for 71 countries during the period 1961 to 1992, find that for lower- to middle developed countries the relationship between economic growth and income inequality forms an inverted U-shape similar to the Kuznets curve, thereby reinforcing the importance of the Kuznets hypothesis. The importance of Kuznets' findings is further argued by Barro (2000), who describes the Kuznets curve as an empirical regularity when discussing income inequality and economic development.

Other research finds limited evidence for the Kuznets curve and argues for alternative nonlinear relationships. Bahmani-Oskooee et al. (2008) examine the relationship between income inequality and national income in 16 countries with cointegration analysis for annual time series data, addressing that previous studies use cross-sectional

data foremost because of lack of proper time series data for individual countries. They find mixed results in both a long-run and short-run timeframe, suggesting limited support for the hypothesis of the Kuznets curve. Instead, they identify that the least developed countries seem to benefit the most from income growth in regard to income distribution and income inequality. Conceição and Galbraith (2015) present an alternative to Kuznets model, claiming that most studies are based on deficient and limited data. In similarity to Bahmani-Oskooee et al. (2008), Conceição and Galbraith (2015) use time series data for a limited set of countries and suggest an augmented Kuznets curve for developed countries with increasing inequality for the highest income countries, thereby suggesting that the inequality increases again with increasing income growth. This pattern is also suggested by List et al. (1999) for highly developed countries, identifying increasing income inequality with economic growth for the most developed nations. Literature also builds on alternate versions of the Kuznets curve. Milanovic (2016), building on works of Piketty and Saez (2003), suggests that the Kuznets curve has fallen out of favor in recent years due to increasing inequality illustrating a second Kuznets curve which is argued to be driven by technological progress, public policies and globalization creating continuous cycles of the Kuznets curve, presented as Kuznets waves.

Rubin and Segal (2015) find that positive changes in growth are associated with increased inequality, investigating the relationship between growth and income inequality in the US between 1953 and 2008. They conclude that the income among top income groups is more sensitive to GDP per capita growth in comparison to income in lower income groups, arguing that the income of the top 1% is almost twice as sensitive to GDP per capita growth compared to the 90% with the lowest income. This analysis is based on the idea that labor and wealth is determined by both current and predicted future growth, with sensitivity to growth varying among different income groups regarding labor, income, and wealth. Rubin and Segal further present two hypotheses to their findings: the wealth hypothesis and the pay-for-performance hypothesis. According to the wealth hypothesis, high-income groups acquire a larger portion of their income from wealth, which is more sensitive to economic growth. The pay-for-performance hypothesis on the other hand is built on the idea that high-income groups acquire a larger portion of their income from equity compensation based on performance, which again is more sensitive to growth.

While the positive relationship between ICTs and economic growth is well established (Vu et al., 2020), studies that investigate the link between economic growth and income inequality have evidenced that the relationship between these two concepts varies across countries belonging to different income groups. Consequently, the studies outlined in this section show that a country's level of income needs to be considered when studying the impact of ICTs on income inequality.

2.4 Synthesis of Literature, Study Aim and Hypotheses Development

Richmond and Triplett (2018), Bauer (2018), Canh et al. (2020), Yilmaz and Koyuncu (2018) and Lin et al. (2017) show that there seem to be differences in the link between ICT and income inequality for low-, middle-, and high-income countries on a global level, a distinction also seen in the regional studies conducted by Cioaca et al. (2020), Yin and Choi (2022) and Ahmad et al. (2022). Similarly, Patria and Erumban (2020) and Ganjoei et al. (2021) identify different results depending on the level of ICT adoption, identifying an inverted U-shape pattern whereby increasing ICT adoption rates initially increase income inequality before reaching a turning point beyond which increased adoption rates start to alleviate income inequality. There is a distinct gap between developed and developing countries regarding ICT, with developed countries having higher ICT use and adoption than developing countries (Billon et al., 2009). Therefore, a country's level of income and its level of ICT adoption seem to affect the relationship between ICT and income inequality, considering most high-income countries have higher ICT adoption rates (Billon et al., 2009).

There is also a link between ICT and income inequality through economic growth. The relationship and positive impact of ICT on economic growth is confirmed in the literature (Vu et al., 2020), with some literature evidencing that low-income countries experience a larger positive effect compared to high-income countries (Appiah-Otoo & Song, 2021; Thompson & Garbacz, 2011). The impact of economic growth on income inequality on the other hand is debated, with the research yielding mixed results and again finding differences depending on country income groups (Bahmani-Oskooee et al., 2008; Kuznets, 1955; Milanovic, 2016). Thus, it can be argued that ICTs have an indirect effect on income inequality through its impact on economic growth, with Untari et al. (2019) identifying a positive indirect effect.

Lastly, the effect appears to differ across different ICTs. The literature largely suggests a significant negative impact on income inequality for most ICT measures (Richmond & Triplett, 2018; Canh et al., 2020; Yilmaz & Koyuncu, 2018). However, studies have also found ICTs that oppose the concluding results by having a positive impact, as for fixed broadband in the study by Richmond and Triplett (2018). This pattern can further be seen when dividing countries into income groups, with specific ICTs only being significant for a certain income group (Richmond & Triplett, 2018; Lin et al., 2017).

In short, the presented literature illustrates that the link between ICT and income inequality appears to depend on the economic development of the country, the level of ICT adoption within the country and indirect effects such as economic growth. Additionally, different ICT variables have been found to have different effects on the outcome of income inequality suggesting that the results will further depend on the ICTs measured (Richmond & Triplett, 2018). Pepper and Garrity (2015) state that there is an apparent paradox between the impact of ICTs on income inequality and further

argue for the importance of additional studies that can improve the understanding of the impact of ICTs on income inequality.

This study aims to improve the understanding of the relationship between ICTs and income inequality by studying how the relationship differs across different ICTs, both globally and for countries with different levels of income. We utilize updated data on a large set of ICT variables to investigate the two following hypotheses:

- **H1:** ICTs alleviate income inequality globally.
- **H2:** The ICT variables with statistically significant impact on income inequality differ across countries belonging to different income groups.

3. Data and methodology

This section begins by providing an overview of the research methodology selected for the study and justifies its choice. It then proceeds to introduce the foundations of the regression model employed followed by a comprehensive description of the model development process, emphasizing the steps undertaken to derive the final model. Subsequently, the section presents the data that was utilized, including its source, collection procedures, and data structuring techniques. Finally, the subsamples are defined, and the software employed for regression analysis is specified.

3.1 Methodology

The methodology used in this study is a quantitative methodology with the use of regression analysis. Edmondson and McManus (2007) discuss methodological fit and the importance of choosing an appropriate research method that aligns with the purpose, theoretical contribution, prior work and context of the study. They present a framework connecting prior work and knowledge of certain fields to the research design and methods. Depending on if the prior research can be viewed as nascent, intermediate or mature the elements of the research methodology should be adapted thereafter, with differences in both research questions, data and data analysis. Edmondson and McManus (2007) conclude that a more mature field should see a larger methodological fit in quantitative data with formal hypothesis testing and statistical analysis, while less mature fields should rely more on qualitative approaches. This is in line with Bell et al. (2022) who argue for the importance of the history of the field when choosing the research methodology. As illustrated in the literature review, extensive research in the field of ICT and its relationship to income inequality has been conducted with different characteristics and conclusions. We therefore conclude that we can both update and build upon knowledge with the use of a quantitative approach in line with previous literature.

Lastly, quantitative methodology in the field of economics can be viewed as common practice with, traditionally, quantitative research being the common methodology used in economic research (Starr, 2014), while qualitative research methods are rarely implemented in economic publications (Lenger, 2019). This further confirms our choice of a quantitative approach in this study.

Quantitative research is deductive in nature and different methods exist to find correlation and statistical significance between concepts (Bell et al., 2022). Bell et al. (2022) explain that quantitative research concepts are usually measured and later classified as independent or dependent variables, and that different statistics and correlation analyses can be used to study the effects and relationship between concepts. Other names for the dependent variable include regressand or measured variable, while the explanatory variable is also known as predictor, regressor or independent variable.

In this study, we aim to investigate the relationship between ICT and income inequality using regression analysis. Gujarati (2022) explains that regression analysis studies the dependent variable using a single or a set of explanatory variables. If more than one explanatory variable is used to predict the outcome of the dependent variable it is called a multiple regression analysis, compared to simple regression analysis which uses a dependent variable and only one explanatory variable. The use of regression analysis techniques have been central to the field of economic statistics, also known as econometrics, for a long time (Sykes, 1993). Furthermore, the use of multiple regression is not only effective in quantifying impacts of simultaneous effects from several explanatory variables on a single dependent variable, but also for dealing with omitted variables bias when only one explanatory variable is of interest (Sykes, 1993).

3.2 Regression Model

In accordance with the aim of the study the specified regression models test the two hypotheses H1 and H2. Gujarati (2022) outlines the basic form of multiple linear regression models with one dependent variable and multiple explanatory variables. Combining this knowledge with the multiple linear regression model form described in Olive (2017) yields the foundation of our regression model presented in equation (1).

$$Y_{it} = X_{it}B + u_i + \varepsilon_{it} \quad (1)$$

The indices i and t denote country and year respectively and B is a vector of coefficients belonging to each of the explanatory variables included in the vector X_{it} . Y_{it} denotes the dependent variable we want to predict being the measure of income inequality, u_i represents the intercept of the model and ε_{it} is the error term.

In the process of building a regression model, Kennedy (2002) argues that one should not worship complexity and instead keep it simple while Feldstein (1982) argues that a useful model should be informative and plausible rather than completely true and realistic. Bell et al. (2022) explain that it is theoretically possible to continuously add more explanatory variables to the equation to increase its explanatory power or goodness of fit, but that the practical utility of such a procedure makes it unjustified. The trade-off between goodness of fit and complexity is also captured by the two concepts of overfitting, where a variable is unnecessarily added to the model, and underfitting, where a necessary variable is omitted (Gujarati, 2022). To avoid over- and underfitting the model and thus keep a good trade-off between goodness of fit and model complexity, Bell et al. (2022) suggest a method called hierarchical regression where explanatory variables are sequentially added to the model. Doing so, it is possible to track how the model's goodness of fit changes as additional explanatory variables are added and facilitates the decision-making of whether to include the additional explanatory variable.

We constructed our model building process with this literature in mind. Initially, the model contained three ICT indicators frequently occurring in the existing literature studying the link between ICT and income inequality: Mobile Cellular Subscriptions per 100 people (MCS), Fixed Broadband Subscriptions per 100 people (FBS) and Individuals Using Internet per 100 (IUI) (Richmond & Triplett, 2018; Tchamyoun et al., 2019a; Ganjoei et al., 2021; Tchamyoun et al., 2019b; Yilmaz & Koyuncu, 2018; Ahmad et al., 2020). The complexity of the model was incrementally increased by first adding two additional ICT indicators in the form of Fixed Telephone Subscriptions per 100 people (FTS) and International Bandwidth Usage (IBU). We then added two additional ICT indicators representing the number of secure internet servers per one million people and the percentage of the population covered by a 3G network, but decided to omit these due to data availability constraints and to ensure that a good balance between goodness of fit and model complexity was maintained. A number of studies that examine the link between ICT and income inequality use a selection of ICT indicators, including several of those previously mentioned, to construct an ICT index (see e.g. Khan et al., 2020; Ahmad et al., 2020; Santos et al., 2017). In this thesis, we choose not to construct an index and thus enable a discussion of the differential impact across different ICTs.

We also added two control variables to the model to improve its explanatory power. First, we added an economic control variable represented by the log of purchasing power parity (PPP) adjusted GDP per capita. The logged value was used to overcome the issue of the nonlinear relationship (Benoit, 2011) between income inequality and GDP per capita that was illustrated in the literature review (see e.g. Barro, 2000; Chen, 2003). Second, we added an educational control variable proxied by the gross secondary school enrollment ratio. The two control variables are abbreviated GDP and SSE respectively. As such, the final model that was used for the regression analysis contains one dependent variable, namely the Gini index, and seven explanatory variables of which five are ICT variables and two are control variables. Descriptive statistics for the full sample of countries as well as the subsamples of countries are presented in Table 1 and Table 3 respectively. The equation for the final model is presented in equation (2).

$$\begin{aligned}
 GINI_{it} = & B_1MCS_{it} + B_2FBS_{it} + B_3IUI_{it} + B_4FTS_{it} + B_5IBU_{it} \\
 & + B_6SSE_{it} + B_7lnGDP_{it} + u_i + \varepsilon_{it}
 \end{aligned}
 \tag{2}$$

Table 1*Descriptive statistics full sample*

Variable	Mean	Std. dev.	Min.	Max.	Description	Source
<i>GINI</i>	37.34	7.92	22.8	63.5	Gini index using disposable income	SWIID
<i>MCS</i>	101.6	38.04	1.47	236.48	Mobile cellular subscriptions per 100 people	WDI
<i>FBS</i>	13.68	13.02	.001	46.34	Fixed broadband subscriptions per 100 people	WDI
<i>IUI</i>	46.04	29.22	0.37	98.26	Internet users per 100 people	WDI
<i>FTS</i>	22.98	18.09	0.02	66.35	Fixed telephone subscriptions per 100 people	WDI
<i>IBU</i>	106,701	585,046.3	44.96	8,267,911	Used capacity (bits/s) of international internet bandwidth per user	ITU
<i>SSE</i>	86.47	27.32	10.59	163.93	Secondary school enrollment (% gross)	WDI
<i>GDP</i>	22,245.3	19,024.79	801.80	118,154.7	Purchasing power parity adjusted GDP per capita	WDI

Notes. Standardized World Income Inequality Database (SWIID), WDI (World Development Indicators), ITU (International Telecommunications Union). Descriptive statistics are calculated using data from all countries and all years.

When building a model, Gujarati (2022) explains that specification biases arise inadvertently and that the main question is not only how to avoid these biases, but how to detect them. The detection of specification errors can be performed through various specification tests (Gujarati, 2022). Hausman (1978) describes specification tests as one of the most important areas in econometrics and presents two different ways of modeling the constant term in the regression model: the fixed effects model and the random effects model. Applying a fixed effects model to panel data allows the entities, in our case countries, to have individually calculated constants whereas the random

effects model assumes that entities' constants are random and normally distributed (Hausman, 1978). Further, to improve the procedure of statistical inference, it is important to ensure conformity with the underlying assumptions of the regression model (Poole & O'Farrell, 1971). One underlying assumption of the linear regression model is that the error terms are homoscedastic (Groß, 2012). Homoscedasticity refers to the case where the variance of the error terms is constant (Olive, 2017) and when this assumption is violated heteroscedasticity is said to be present in the data (Poole & O'Farrell, 1971). Another underlying assumption is that the error terms are uncorrelated with each other (Groß, 2012). In panel data, error terms can be correlated across time and entities (Poole & O'Farrell, 1971; Driscoll & Kraay, 1998).

In this study we perform several regressions: one to study the relationship between ICT and income inequality on a global level and three separate regressions, one for each group of countries, to study how the relationship differs between low-, middle-, and high-income countries. The difference between the regression for the full sample and the subsamples relate to the number of specification tests that were conducted and how the results from these tests were incorporated.

For the regression that was used to study the relationship on a global level, we first performed the Hausman test to determine between the fixed effects and random effects specifications and rejected the null hypothesis in favor of the alternative hypothesis that a fixed effects specification is preferred. Second, we performed a modified Wald test and rejected the null hypothesis that the dataset is homoscedastic. Third, we performed a Wooldridge test and rejected the null hypothesis of no serial correlation. Lastly, we performed a Pesaran's test and rejected the null hypothesis of weak cross-sectional dependence in favor of the alternative hypothesis of strong cross-sectional dependence. To overcome these issues, we ran our regression model with Driscoll and Kraay standard errors which are robust to heteroscedasticity, serial correlation, and cross-sectional correlation (Driscoll & Kraay, 1998). Test results are presented in Table 2.

Table 2

Specification tests full sample

	Test statistic	<i>p</i> -value
Hausman test	66.03	0.0000
Modified Wald test	1.3×10^6	0.0000
Wooldridge test	700.84	0.0000
Pesaran's test	2.35	0.019

Note. The null hypotheses of the respective specification tests were rejected if the *p*-values were below 0.05.

For the three regressions that were used to study how the relationships differ between low-, middle-, and high-income countries, we only performed the Hausman specification test due to time constraints. For the samples of low-, and high-income countries we failed to reject the null hypothesis and thus applied the random effects specification. For the sample of middle-income countries, we rejected the null hypothesis and applied a fixed effect model.

Table 3

Descriptive statistics subsamples

Variable	<i>High-income countries</i>		<i>Middle-income countries</i>		<i>Low-income countries</i>	
	Mean (Std. dev.)	Min Max	Mean (Std. dev.)	Min Max	Mean (Std. dev.)	Min Max
<i>GINI</i>	32.07 (6.33)	22.8 49.9	41.12 (7.39)	24.6 63.5	40.91 (6.18)	26.7 60.4
<i>MCS</i>	122.57 (23.20)	61.70 236.49	111.60 (31.16)	33.97 205.04	66.01 (33.32)	1.47 164.54
<i>FBS</i>	26.52 (9.02)	2.36 46.34	8.99 (6.40)	0.15 32.58	1.10 (1.75)	0.001 10.18
<i>IUI</i>	72.73 (15.87)	28.3 98.26	41.96 (18.14)	6.11 80.14	15.06 (13.59)	0.37 64.5
<i>FTS</i>	38.56 (14.20)	6.86 66.35	20.20 (9.25)	6.29 46.81	5.22 (7.70)	0.02 37.84
<i>IBU</i>	226,699 (898,357)	1,298 8,267,911	41,540 (54,806)	44.96 390,848	7,192 (9,551)	56.00 58,674
<i>SSE</i>	105.31 (15.18)	68.78 163.93	92.20 (13.13)	44.99 128.92	57.28 (23.75)	10.60 99.61
<i>GDP</i>	40,137 (16,491)	15,441 118,155	15,315 (5,172)	4,974 27,583	5,038 (3,594)	802 15,302

Note. Descriptive statistics are calculated using data from all countries and all years.

3.3 Data

The regression model uses a short, unbalanced panel of data consisting of 120 countries for eleven years between 2007 and 2017. The panel is defined as short due to the number of countries being greater than the number of time periods, while the panel is unbalanced because each country does not have the same number of observations (Gujarati, 2022). According to Baltagi (2008) panel data has several benefits over both

cross-sectional data and time-series data. Firstly, panel data can take heterogeneity from the countries and time into account with subject-specific variables. Secondly, through combining a time series of cross-sectional observations, panel data can be argued to give more informative data in addition to higher efficiency. Lastly, according to Baltagi (2008), panel data can be argued to be better suited for investigating dynamic changes and measuring effects that cannot otherwise be detected. In addition to the many benefits of panel data, it is also a method frequently used in the literature and in similar studies. Panel data has been used in the studies by Richmond and Triplett (2018), Canh et al. (2020), Patria and Erumban (2020) and Tchamyoun et al. (2019a) to name a few.

To be able to quantitatively study a concept, it needs to be measured (Bell et al., 2022). Several measures exist for measuring income inequality, inter alia the Atkinson index, Palma ratio and Theil indices but the by far most commonly employed measure for income inequality across several fields of study is the Gini coefficient (De Maio, 2007). The Gini coefficient is a single summary statistic of income distribution derived from the Lorenz curve. The Lorenz curve shows the cumulative percentage of total income earned by a cumulative percentage of the population. When income is perfectly equally distributed, any cumulative percentage of the population earns a corresponding percentage of total income. For example, the poorest 25% of the population earns 25% of total income, the poorest 50% of the population earns 50% of total income and so forth. In the scenario of perfectly equally distributed income, the Lorenz curve forms a straight line with slope coefficient equal to 1 also referred to as the line of equality. The Gini coefficient essentially measures the deviation from the line of equality and takes values between 0 and 1 where 0 represents the scenario where income is perfectly equally distributed and 1 represents the scenario where all income belongs to a single individual (De Maio, 2007). The Gini coefficient is commonly presented as a percent, in which case it takes values between 0 and 100 and is referred to as the Gini index (Solt, 2020).

Several sources can be utilized for collecting country data on the Gini coefficient globally or for different regions and sets of countries, including the United Nations University's World Income Inequality Database, the OECD Income Distribution Database, Eurostat, and the World Bank (Gimpelson & Treisman, 2017). Data from all these, and many other sources, are compiled and standardized in the Standardized World Income Inequality Database (SWIID) which seeks to maximize breadth of coverage and comparability between countries (Solt, 2020). Consequently, it has become the preferred source of income inequality data for many fields of research that require extensive cross-national data (Solt, 2020). Based on the purpose and methodology of this study we have chosen to use Gini index data from the SWIID. Additionally, by using this data set we improve the comparability with previous literature given that many existing studies that explore the link between ICT and income inequality use this data set as well.

The SWIID provides estimates of the Gini index based on three different definitions of income: market income, gross income and disposable income. Market income is defined as pre-tax and pre-transfer; gross income is defined as pre-tax post-transfer; and disposable income is defined as post-tax and post-transfer. As such, the Gini index based on disposable income represents the distribution of money in people's pockets and Solt (2020) therefore argues that this Gini index variant is most appropriate for most researchers. In this study, we follow this recommendation and use the Gini index based on disposable income as the measure of income inequality.

Data for all indicators and control variables was downloaded from the World Development Indicators (WDI) database, except for data on IBU which was downloaded directly from the ITU World Telecommunication/ICT Indicators Database. The original source of data for all ICT indicators is the ITU World Telecommunication/ICT Indicators Database. The ITU World Telecommunication/ICT Indicators database contains yearly information on a wide set of ICT indicators for more than 200 countries and has therefore become the preferred database for research where ICT indicators are required. The characteristics of the dataset are particularly well-suited for this thesis since the quantitative analysis requires a large set of complete data.

In establishing our dataset, we began by downloading data covering as many years as possible for each of the variables that were chosen to be included in the model. By analyzing the availability of data, we found that the number of missing observations for the variables included in the model significantly increased from 2017 to 2018 and, further, that data on international bandwidth usage was only available from 2007. Therefore, the time period in this study was chosen to be the eleven years spanning from 2007 to 2017. Still, the resulting dataset included missing observations. There are several methods available for dealing with missing data, and in this study we choose to apply listwise deletion. Listwise deletion means removing all incomplete observations and while this method underperforms compared to other conventional methods such as imputation in terms of maximizing the use of available data, it is probably the safest method since it yields accurate estimates of the true standard errors and thus provides an honest method for handling missing data (Allison, 2001). Additionally, to be able to perform specification tests and thus improve conformity with the underlying assumptions of our regression model, we entirely excluded all countries that did not have complete observations for at least 4 years. As a result, we ended up with an unbalanced dataset of 1078 observations for 120 countries. The total number of countries and observations deleted from the samples is illustrated in Table 4.

Table 4*Number of countries and observations deleted from each sample*

	<i>High-income countries</i>	<i>Middle-income countries</i>	<i>Low-income countries</i>	<i>Full sample</i>
Countries	12	18	33	63
Observations	132	162	314	608

Note. Countries and observations were deleted in several steps, and the table illustrates the total number deleted in the final dataset in relation to the original dataset.

We use the 2022-2023 World Bank classification of countries to create our three subsamples of countries. The World Bank assigns countries to one of the four categories low-income, lower-middle-income, upper-middle-income and high-income based on their GNI per capita measured in current USD using the Atlas method (Hamadeh et al., 2023). The definitions of our subsamples are as follows. Countries included in the low-income sample are those defined by the World Bank as low-income and lower-middle-income, countries included in the middle-income sample are those defined by the World Bank as upper-middle-income, and countries included in the high-income sample are those defined by the World Bank as high-income. As such, the definition of our subsamples is consistent with existing literature (Richmond & Triplett, 2018). Further, grouping low- and lower-middle-income countries ensures that our subsamples include a sufficient number of countries and observations. The number of observations and countries included in each of our subsamples are as follows. The low-income subsample consists of 343 observations from 43 countries, the middle-income subsample consists of 292 observations from 32 countries, and the high-income subsample consists of 443 observations from 45 countries.

3.4 Software

Having downloaded and structured the data in Microsoft Excel, it was imported to Stata where the regression analysis was performed. Firstly, the dataset was declared as a panel using the function ‘xtset’. Initially, the commands that were used to perform the regressions on the full sample as well as the three subsamples was first ‘regress’ and then ‘xtreg’. Thereafter, we performed the Hausman test using the command ‘hausman’ and incorporated the results of these tests by re-running the models using ‘xtreg, re’ or ‘xtreg, fe’ depending on if the null hypothesis of the tests was rejected or not.

Thereafter we proceeded to conduct three additional tests on the full sample estimation results. The modified Wald test was performed using ‘xttest3’, followed by the Wooldridge test through the command ‘xtserial’ and lastly the Pesaran’s test using the command ‘xtcd2’. As previously mentioned, the results of the tests indicated the presence of heteroskedasticity, autocorrelation and cross-sectional correlation and we

therefore decided to run the regression once more by incorporating Driscoll and Kraay standard errors using the command ‘xtscc’.

4. Results

This section first presents the estimation results for the regression models using the full sample as well as an explanation of how to interpret the results. Subsequently, the estimation results for the regression models using the three subsamples are provided, followed by a comparison of the results that were obtained for the three subsamples.

4.1 Global Level

Estimation results for the full sample are presented in Table 5. First, by studying the p-values for the ICT variables in Table 5, we find statistically significant relationships at the 0.05 confidence level between GINI and MCS, IUI, FTS, and IBU while the relationship between GINI and FBS is insignificant. Further, the signs of the coefficient values for these ICTs show that the relationship between three of four ICT variables, namely MCS, IUI and FTS, are negative such that an increase of these variables are associated with lower values of GINI. Similarly, the positive coefficient value that has been assigned to the IBU variable indicates that an increase in this variable is associated with higher values of GINI. Recalling that a lower GINI corresponds to lower income inequality, our results indicate that among the four ICT variables that exhibit statistically significant relationships with GINI, three decrease income inequality while one increases income inequality.

Studying the coefficient values also facilitates an analysis regarding the relative strengths of the effects exerted by the ICT variables on GINI. The largest absolute coefficient value belongs to FTS whereby a one point increase in this variable corresponds to a 0.0493 point decrease in GINI. Similarly, a one point increase in IUI and MCS correspond to 0.0295 and 0.0038 point decreases in GINI respectively, while a one point increase in IBU is associated with a 1.3×10^{-7} point increase in GINI.

Further, our results indicate that education, proxied by secondary school enrollment, does not exhibit a statistically significant relationship with GINI while our economic control variable, proxied by the log transformed value of PPP adjusted GDP per capita, does. Given that the economic control variable is log transformed, the interpretation of its assigned coefficient value differs from the other explanatory variables. Rather than showing how much a one *point* increase in the explanatory variable causes the dependent variable to change, the coefficient assigned to a log transformed explanatory variable explains how a one *percent* increase in the explanatory variable causes the dependent variable to change. More precisely, our results show that a one percent increase in PPP adjusted GDP per capita corresponds to a 0.0129 point decrease in GINI.

Table 5*Estimation results for the full sample*

Variables	Coefficient	Std. error	t	p	95% CI
<i>MCS</i>	-0.0038***	0.0010	-3.64	0.005	[-0.0061, -0.0015]
<i>FBS</i>	0.0080	0.0164	0.49	0.635	[-0.0286, 0.0446]
<i>IUI</i>	-0.0295***	0.0057	-5.18	0.000	[-0.0421, -0.0168]
<i>FTS</i>	-0.0493***	0.0047	-10.43	0.000	[-0.0599, -0.0388]
<i>IBU</i>	1.3×10^{-7} ***	2.4×10^{-8}	5.42	0.000	$[7.7 \times 10^{-8}, 1.8 \times 10^{-8}]$
<i>SSE</i>	-0.0056	0.0035	-1.60	0.140	[-0.0135, 0.0022]
<i>GDP</i>	-1.2976***	0.3098	-4.19	0.002	[-1.9879, -0.6072]
<i>Constant</i>	52.9628***	2.6726	19.82	0.000	[47.0080, 58.9178]

Note. Coefficient estimates with *, **, *** representing statistical significance at 0.1, 0.05 and 0.01, respectively.

4.2 Low-, Middle-, and High-Income Samples

Estimation results for each of the three subsamples are presented in Table 6. In our sample of high-income countries, MCS and FTS display statistically significant relationships with income inequality at the 0.05 confidence level while FBS, IUI, and IBU do not. As indicated by the negative sign of the coefficients assigned to both MCS and FTS, increases in these explanatory variables are associated with decreases in GINI. Further, a comparison of the values of the coefficients assigned to the MCS and FTS variables suggest that a one point increase in FTS corresponds to a larger decrease in GINI compared to the MCS variable.

For our sample of middle-income countries, the results show that three of five ICT variables have statistically significant relationships with GINI at the 0.05 confidence level: FBS, IUI and FTS. The sign of the coefficients assigned to these variables indicate that an increase in FBS is associated with an increase in GINI, while increases in IUI and FTS correlate negatively with GINI. Despite the opposite directions of the

effects caused by FBS and FTS on GINI, the absolute value of their coefficients suggest that their impacts are of similar magnitude, with the influence of IUI being comparatively weaker among the three variables.

For our sample of low-income countries, the results reveal two explanatory variables, namely MCS and FTS, that exhibit statistically significant relationships with GINI at a 0.05 confidence level. Notably, an increase in either of these variables is linked to a decrease in the GINI. The impact of the FTS variable is found to be more pronounced compared to the MCS variable, indicating a stronger effect of FTS on reducing GINI.

A comparison of the results across the different subsamples reveal that the impact of the ICT variables appears to differ. Only one ICT variable, FTS, consistently demonstrates statistically significant relationships with GINI across all subsamples at a 0.05 confidence level. Specifically, an increase in FTS is consistently associated with a decrease of GINI in low-, middle-, and high-income countries. Additionally, and perhaps unsurprisingly given these results, the FTS variable displays a statistically significant relationship with GINI for the full sample as well. The only ICT variable apart from FTS that displays statistically significant relationships across more than one subsamples is MCS which is negatively correlated with GINI in both low- and high-income countries while statistically insignificant for middle-income countries.

Table 6

Estimation results for the subsamples

Variables	<i>High-income countries</i>		<i>Middle-income countries</i>		<i>Low-income countries</i>	
	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error
<i>MCS</i>	-0.0118***	0.0032	0.0021*	0.0038	-0.0097***	0.0036
<i>FBS</i>	-0.0086	0.0159	0.1089***	0.0307	-0.0687	0.0620
<i>IUI</i>	-0.0033	0.0079	-0.0543***	0.0096	-0.0171*	0.0095
<i>FTS</i>	-0.0588***	0.0087	-0.0982***	0.0220	-0.0667***	0.0288
<i>IBU</i>	1.5×10^{-7} *	7.8×10^{-8}	-1.3×10^{-6}	1.7×10^{-6}	-1.2×10^{-5}	8.2×10^{-6}
<i>SSE</i>	-0.0228***	0.0059	-0.0336***	0.0112	0.0433***	0.0100
<i>GDP</i>	-2.7535***	0.5479	-3.8050***	1.1991	-0.3958	0.6813
<i>Constant</i>	68.3263***	5.6086	83.7448***	11.1284	43.1172***	5.3622

Note. Coefficient estimates with *, **, *** representing statistical significance at 0.1, 0.05 and 0.01, respectively.

5. Discussion and Analysis

In this section, we utilize existing literature to discuss our results. Naturally, given the varying outcomes reported across different research studies, we have observed results that both support and contradict existing findings. By drawing on the explanations provided in the existing literature and analyzing them in reference to our observations for both the full sample and the three subsamples, we are able to assert whether our hypotheses should be rejected or accepted.

5.1 Global level

The impact of ICTs on income inequality has been extensively studied, with varying outcomes reported across different research studies. In our estimation model, we have observed results that both support and contradict existing findings. In the previous section, we presented the results of our regression analysis, which indicated significant relationships for four out of five ICT variables: MCS, IUI, and FTS demonstrated a significant negative impact on GINI, while IBU exhibited a positive correlation and FBS did not show any significant impact. Furthermore, when considering the control variables, we found that SSE yielded an insignificant result, whereas GDP demonstrated a negative and significant effect. These findings imply that mobile usage, internet usage and fixed telephone usage together with GDP growth would be negatively correlated with the Gini index, while international bandwidth would be positively correlated. For fixed broadband usage and secondary school enrollment no significant results were found. To comprehensively study the overall effect of ICTs on income inequality at a global level, we will now proceed to analyze each ICT measure individually and compare our results to both the literature and the subsample results.

The estimation results for mobile usage, MCS, illustrate a significant negative relationship between mobile usage and income inequality. This relationship has been investigated in several studies in the literature, with Richmond and Triplett (2018), Canh et al. (2020), Yilmaz and Koyuncu (2018), Santos et al. (2017) and Shah and Krishnan (2023) all examining the impact of mobile usage on the Gini index at a global level, finding various results. Richmond and Triplett (2018), Canh et al. (2020), Yilmaz and Koyuncu (2018) and Shah and Krishnan (2023) find, in similarity to our results, a significant negative correlation between mobile usage and the income inequality, suggesting that mobile usage contributes to an alleviation of income inequality. Santos et al. (2017), examining both ICT and infrastructure variables while controlling for human capital, argues that mobile usage together with several other ICT measures have a positive impact on income inequality. They use a panel of data for 111 countries over

a period from 1960 to 2003, a much earlier and longer period compared to other literature on the topic which could be a potential reason for the conflicting result. Furthermore, when grouping old and modern ICT they find older ICT being negatively correlated while no significant effects are found for modern ICTs, as mobile usage, which is argued to speak against claims that modern ICTs are increasing inequality.

Results obtained from the subsample regression further confirms a negative impact on income inequality from mobile usage. Mobile usage was found to be significantly negative for both low- and high low-income countries, and insignificant for middle-income countries. These results are in line with the literature where only Yin and Choi (2022) find a positive effect for high-income countries from mobile usage on income inequality, and several other studies (see e.g. Adams & Akobeng, 2021; Asongu, 2015; Mutiiria et al., 2020) indicate a negative impact. The reasons for income inequality alleviating effects from mobile usage is argued by Canh et al. (2020), explaining that internet and mobile usage can help in improving ways of finding jobs, increasing business opportunities, and boosting education. Thus, we suggest that our results regarding mobile usage's effect on income inequality seem to be in line with the literature on the topic and thereby emphasizing a negative impact on a global level.

In contrast to mobile usage our estimation results for fixed broadband usage, FBS, is found to be insignificant. The literature on fixed broadband usage also indicates conflicting results similar to literature on mobile usage, with an overall negative impact on income inequality and some studies indicating the opposite relationship. Yilmaz and Koyuncu (2018) and Shah and Krishnan (2023) find a negative impact from fixed broadband usage, while a positive effect and an increase in income inequality from fixed broadband usage is found by Richmond and Triplett (2018). Richmond and Triplett (2018) concluded that the income inequality increasing effects from fixed broadband usage also was larger than the income decreasing effects from MCS, resulting in a net positive effect if both variables are increased by one standard deviation. They suspect that the difference between the variables' impact on income inequality originates from different levels of accessibility to the technologies due to their cost structure, and foremost the fixed costs associated with the technologies. A difference however between the studies by Yilmaz and Koyuncu (2018) and Richmond and Triplett (2018) is the use of a smaller set of countries by Richmond and Triplett (2018), while Yilmaz and Koyuncu (2018) use a larger set of countries and several income inequality indicators, including the Gini index.

The estimation results from the subsamples indicate a positive significant result for middle-income countries for fixed broadband usage, while no significant results are found for the other subsamples. Furthermore, the literature in regional studies and from subsamples also indicate varied results for fixed broadband usage. Yin and Choi (2022) find a positive effect from fixed broadband usage also for high-income countries while Richmond and Triplett (2018) find a positive effect for both middle- and high-income countries. On the other hand, studies by Adams and Akobeng (2021), Mutiiria et al.

(2020) and Ahmad et al. (2022) indicate a negative effect from fixed broadband usage on income inequality. These studies differ from the studies previously mentioned in that they focus on subsamples with mostly developing countries, which could be a reason for the different results achieved. Thus, considering both our estimation results and the literature we suggest that the impact of fixed broadband usage on income inequality on a global level is ambiguous.

The variable for internet usage, IUI, was found to be negatively significant and decreasing income inequality. This is also suggested in the literature, with Canh et al. (2020), Yilmaz and Koyuncu (2018), Lin et al. (2017) and Shah and Krishnan (2023) all finding a negative relationship on a global level between internet usage and income inequality. Santos et al. (2017) however find a positive relationship, which could be because of the longer and earlier time period used, considering the fact that the accessibility of the internet was low in the 60s and 70s and grew rapidly in later years (Glowniak, 1998). The subsample results confirm a negative impact from internet usage, with a negatively significant relationship identified for middle-income countries. This is further illustrated by Yin and Choi (2022) for high- and middle-income countries combined and middle-income countries by its own, while they find a positive relationship for high-income countries. Lin et al. (2017) on the other hand find a negative impact from internet usage on income inequality for high-income countries but a positive impact for low-income countries. Other studies, including Cioaca et al. (2020) and Adams and Akobeng (2021) to name a few, find negative impacts from internet usage, which seem to be the general pattern for most studies. There can be several reasons for internet usage decreasing income inequality, Lin et al. (2017) explains how improving the digital divide can be an effective method for alleviating income inequality, with internet use effectively increasing income by spreading new low cost technologies. Thus, we suggest that both our results and literature argue for a negative impact on income inequality from internet usage on a global level.

The ICT variable fixed telephone usage, FTS, was found to have a significant negative impact on income inequality, a result similar to results obtained for mobile usage and internet usage. Fixed telephone usage is however not as pronounced in literature compared to other ICT measures as mobile usage, fixed broadband usage and internet usage, with only two studies on a global level including fixed telephone usage. Santos et al. (2017) find a positive impact from fixed telephone usage on income inequality while Canh et al. (2020) don't present any significant results. As mentioned, Santos et al. (2017) use a different time period compared to many other studies and their results tend to not be in line with other literature. The fixed telephone is an older technology compared to many other ICTs, and classified as an old ICT by Santos et al. (2017) when comparing old and modern ICT. The different results presented by Santos et al. (2017) can therefore be due to the different time period used, and that fixed telephones were less accessible and served a different role 60 years ago compared to today, when modern ICTs like mobile phones and internet are spreading rapidly across countries (Yilmaz and Koyuncu, 2018).

The estimation results on fixed telephone usage for the subsamples confirm the results obtained for the full sample, with all three subsamples indicating a significant negative impact. This is further shown in regional studies, with Ahmad et al. (2022) and Mutiiria et al. (2020) also finding negative relationships for fixed telephone usage in their studies. Thus, we suggest that the impact of fixed telephone usage on income inequality is negative and that increases in fixed telephone usage decreases income inequality globally. However, it is noted that the results might depend on the time period examined, and that the effect from fixed telephone usage might have been different before the entering of more modern ICTs.

The last ICT measure examined was international bandwidth usage, IBU, which was found to be significantly positive for the full sample and insignificant results were found for the subsamples. In addition international bandwidth usage obtains a smaller value for the coefficient compared to the other variables, with a one unit increase having a small increasing effect on income inequality. This smaller value could be derived from the characteristics of the measure, with international bandwidth usage being represented by used capacity (bits/s) of international internet bandwidth per user, compared to the other measures using the number of subscriptions per 100 people. In contrast to the other ICTs, international bandwidth usage's impact on income inequality has not previously been studied in the literature and therefore our results on this specific variable can not be compared to the previous studies. Thus, it is suggested that international bandwidth usage could have a potential positive impact on income inequality, however further research on this ICT would have to confirm our results.

Lastly, the control variable for secondary school enrollment, SSE, is found to be statistically insignificant while GDP is negatively significant. The subsamples indicate a similar result, with secondary school enrollment being negatively significant for middle- and high-income countries, but a positive significant for low-income countries. GDP is found to be negatively significant except for low-income countries where it is not significant. The results found on GDP argue for its income inequality alleviating effect, however the literature presents various results as illustrated in Section 2.4. The GDP coefficient is further found to be large, at -1.2976, indicating that a one percent increase in GDP would decrease income inequality by 0.0129 units.

5.2 Low-, Middle-, and High-Income Samples

Following the analysis of the ICT impact on income inequality on a global level an analysis of income groups is conducted. The impact of the five ICT measures on income inequality in low-, middle-, and high-income groups are analyzed respectively to investigate the differences between the impact in the various groups.

Our estimation results presented in Section 4.2 indicate that increases in both mobile and fixed telephone usage decrease income inequality in high-income countries.

Starting with mobile usage, our results are consistent with those obtained by Canh et al. (2020) but appear to be incoherent with Yin and Choi (2022) who find that mobile usage increases income inequality for high-income countries. However, comparing our results with these studies requires an analysis of the respective populations from which the samples of high-income countries are created. Canh et al. (2020) create their sample of high-income countries from the same population of countries as we do in this study, namely high-income countries globally, while Yin and Choi (2022) study high-income G20 countries. Consequently, the results are not necessarily contradictory since they may be true simultaneously; some of the effects of mobile usage that increase income inequality could be particularly strong in high-income G20 countries compared to high-income countries globally. Evidence in favor of this possibility is presented by Yin and Choi (2022) who mention that the digital technology development in G20 countries may be skill-biased and generate higher demand, and thus higher income, for skilled workers in these countries. Further, Canh et al. (2020) is the only study, to our knowledge, that specifically examines the effect of fixed telephone usage in high-income countries. Albeit statistically insignificant, Canh et al. (2020) finds that increased fixed telephone usage decreases income inequality in high-income countries and thus largely agrees with our results. As such, our statistically significant results for high-income countries appear to be consistent with the existing literature.

In terms of the effect of fixed broadband usage in high-income countries the estimation results produced in this study, namely that the effect of fixed broadband usage is insignificant, appear to differ from results obtained in the existing literature with both Richmond and Triplett (2018) and Yin and Choi (2022) obtaining results indicating that fixed broadband usage exacerbates income inequality in high-income countries. A possible explanation for these deviating results is that the analyses conducted by Richmond and Triplett (2018) and Yin and Choi (2022) utilize data that tracks back to 2001 and 2002, respectively. This is a key difference since these studies capture the initial increase in the adoption of fixed broadband; WDI data shows that the number of fixed broadband subscriptions per 100 people in high-income countries globally increased from 3.4 in 2001 to 21.4 in 2007 and then to 32.8 by 2017 (World Bank, 2023). Previous studies have shown that the effect of ICTs on income inequality follows an inverted U-shape such that increased ICT adoption initially increases income inequality before reaching a threshold value after which it starts to decrease income inequality (Patria & Erumban, 2020; Ganjoei et al., 2021). The presence of such a relationship could explain the positive relationship between fixed broadband and income inequality observed by Richmond and Triplett (2018) and Yin and Choi (2022) since these studies utilize datasets that capture the large initial increase in the adoption rate where the inverted U-shape theory predicts a positive impact. Such a relationship could further explain our estimation results since if our dataset includes observations on both sides of the threshold value where the direction of the relationship changes our estimation model would struggle to infer a linear trend between the two variables, thus leading to statistical insignificance.

For our two ICT variables individual internet usage and international bandwidth usage we obtain insignificant results and are thus unable to deduce if the effects are negative, positive or none. Interestingly, our review of the literature resulted in a similar lack of clarity since there are studies who find that the effect of internet on income inequality in high-income countries is both negative (Canh et al., 2020); Lin et al., 2017), positive (Yin & Choi, 2022) and insignificant (Richmond & Triplett, 2018). As previously mentioned both negative and positive effects are theoretically supported and the dispersion and lack of coherence among existing studies, which are partly reinforced by our results, may indicate that the nature of the impact may depend on conditional effects or interactions with other concepts. For example, Yin and Choi (2022) find that the interaction between internet usage and foreign direct investments is associated with a decrease in income inequality, while the interaction between internet usage and trade openness increases income inequality. It has also been found that a minimum level of political stability is required for internet usage to decrease income inequality and that the effect becomes greater when urbanization rates increase (Richmond & Triplett, 2018).

In short, we are able to explain our results for the high-income sample by analyzing them in light of existing literature and the concepts discussed therein, thus indicating that ICTs alleviate income inequality in high-income countries by providing rigid evidence that mobile and fixed telephone usage alleviates income inequality while the impact of fixed broadband and internet usage are less concise.

Contrary to the results obtained for the high-income sample, we find that both fixed broadband and individual usage of the internet have statistically significant effects on income inequality in middle-income countries. Additionally, fixed telephone usage appears to decrease income inequality in this set of countries, with mobile usage and international bandwidth exhibiting statistically insignificant relationships. Starting with fixed broadband, our results indicate a positive impact such that increases in fixed broadband usage increases income inequality. Richmond and Triplett (2018), who obtain similar results, argue that this impact is due to the relatively higher cost of the technology compared to other ICT which causes differential access where only richer households can reap the economic benefits of access to fixed broadband, thus widening the income gap. On the contrary, Yin and Choi (2022) find that increased fixed broadband usage decreases income inequality in middle-income G20 countries and speculate that the evolution of digital technologies create new job opportunities. However, the effect that Yin and Choi (2022) observe is much weaker compared to Richmond and Triplett (2018) and those obtained by our estimations. Additionally, the sample of middle-income countries in Yin and Choi (2022) is in turn a subsample of the middle-income countries included in our study. Thus, without questioning the authenticity of the results obtained by Yin and Choi (2022), it appears unlikely that the results they obtain for fixed broadband in middle-income G20 countries are sufficiently strong to impact the legitimacy of the results obtained by Richmond and Triplett (2018) and this study given that we study middle-income countries globally.

With regards to individual internet usage in middle-income countries, the literature is more extensive and coherent with only one study recording a statistically insignificant result (Richmond & Triplett, 2018). Lin et al. (2017) argue that increased individual internet usage accelerates technological progress and simultaneously decreases the cost of existing technologies, thus reducing the digital divide and thereby income inequality. Yin and Choi (2022) underline the importance of closing the digital divide and argue that the expansion of the internet can contribute positively to the inclusion of previously excluded individuals and companies, thus allowing them to participate in the global economy. It has also been argued that active measures to increase individual internet usage should be part of economic policies that aim to decrease income inequality in low- and middle-income countries (Canh et al., 2020). Thus, much of the literature tends to agree with the results obtained in our study, indicating that the effect of individual internet usage efficiently decreases income inequality in middle-income countries.

For mobile usage in middle-income countries, existing literature indicates that the impact on income inequality tends to be negative (Canh et al., 2020; Richmond & Triplett, 2018), while our results indicate an insignificant impact. However, as illustrated by the estimation results for their high-income sample, Richmond and Triplett (2018) argue that once mobile usage reaches its saturation level the effect of the technology may become insignificant. By analyzing mobile usage for our sample of middle-income countries, we find that the average number of mobile cellular subscriptions per 100 people approached 120 in 2012, a point at which it stabilized for the upcoming years. Hence in our sample of middle-income countries mobile usage was at its saturation level during the majority of the time period of our analysis. By comparison, the studies by Canh et al. (2020) and Richmond and Triplett (2018) utilized data from 2002-2014 and 2001-2014, respectively, time periods during which most middle-income countries were yet to reach their saturation levels, thereby explaining the significance of the results obtain by Canh et al. (2020) and Richmond and Triplett (2018) while also explaining the insignificance of our results.

Our results for fixed telephone and international bandwidth usage in middle-income countries are difficult to assess using existing literature given the scarcity of studies on these specific topics. We find that fixed telephone usage decreases income inequality in middle-income countries while Canh et al. (2020) find a negative but insignificant impact on income inequality in their sample of low- and middle-income countries, thus only partly agreeing with our findings. Additionally, a study of middle-income countries in Africa showed that the spread of fixed telephones led to an improved standard of living (Chavula, 2013). While evidence in favor of the inequality-reducing effect of fixed telephones in middle-income countries is not exhaustive, the complete absence of evidence in favor of the opposite effect appears to indicate that our findings are reasonable. Based on the argument that increased internet usage facilitates the participation of previously excluded individuals in the global economy (Yin & Choi,

2022), we would have expected international bandwidth usage to exert a negative impact on income inequality. However, the statistical insignificance of our estimation results and the lack of existing literature prevent such inferences.

Our analysis of middle-income countries shows that the general impact of ICTs on income inequality is difficult to assess. While the cost structure of fixed broadband is found to exacerbate income inequality in middle-income countries by not being accessible to all, this effect is counteracted by the alleviating impact from fixed telephone and individual internet usage. The assessment is further complicated by the lack of an effect from mobile, which is attributed to the already high adoption rates, and the absence of literature examining the impact of international bandwidth usage. In sum, given the strength of the impacts from the statistically significant ICT variables presented in Table 6, our results and analysis indicate an overall negative impact from ICTs in middle-income countries as well.

Similar to the high-income sample, our estimation results for the low-income sample indicate negative effects of mobile and fixed telephone usage on income inequality. In terms of the effect of mobile, our results are different to those obtained by Richmond and Triplett (2018) who do not find a statistically significant impact, arguing that the absence of a significant effect is partly due to the lack of political stability present in many low-income countries. However, evidence of the negative impact of mobile usage on income inequality in low-income countries is presented by Canh et al. (2020) as well as by studies that examine the effect in specific geographical regions that mainly consist of countries that fall into our sample of low-income countries (Adams and Akobeng, 2021; Asongu, 2015; Tchamyou et al., 2019a). Interestingly, Adams and Akobeng (2021) find that the negative impact of mobile usage is consistent across different levels of political stability, thus contesting the argument posed by Richmond and Triplett (2018). Additional evidence of the negative impact of mobile usage in low-income countries is provided by Mutiiria et al. (2020) and Ahmad et al. (2022) who find negative relationships between ICT indices, which include mobile usage, and income inequality for low-income countries in South Asia and sub-Saharan Africa, respectively. Since the ICT indices that are constructed in these studies also consist of fixed telephone usage, Mutiiria et al. (2020) and Ahmad et al. (2022) underline the negative impact of this technology in low-income countries as well. Meanwhile, it is important to note that while the studies that focus on specific geographical regions are useful for the analysis of our results, they can only partly confirm their legitimacy given that our sample of low-income countries covers geographical regions beyond Africa and South Asia.

We obtain insignificant results for fixed broadband usage, individuals using the internet, and international bandwidth usage. The absence of an impact of fixed broadband in low-income countries is also recorded by Richmond and Triplett (2018) who argue that the adoption rates of fixed broadband have not yet reached a level where changes can have an appreciable impact on income inequality. Studying the evolution

of the average number of fixed broadband subscriptions per 100 people in our low-income sample, we find that it increased from a mere 0.3 in 2007 to 2.4 in 2017, thereby justifying the argument posed by Richmond and Triplett (2018) that the lack of an effect is caused by low adoption rates. Moreover, the insignificant effect of internet usage can be explained by employing a reasoning similar to that of Patria and Erumban (2020) and Ganjoei et al. (2021) who argue for the inverted U-shape relationship between the adoption rate and income inequality. For our sample of low-income countries, the average number of individuals using the internet per 100 people increased from 6.2 in 2007 to 14.3 in 2012 and 35.7 in 2017. Thus, for a large portion of the duration our dataset covers, the adoption rate of the internet was between 14.3% and 32.1%, which Ganjoei et al. (2021) argues to be the interval where the impact of internet usage on income inequality is weakest. Further, it is likely that our sample of low-income countries includes observations that indicate both positive and negative impacts given that the threshold value of 25% presented by Patria and Erumban (2020) was passed during the time period of our dataset, thus explaining the inability to infer a statistically significant linear effect of internet usage on income inequality. It is important to acknowledge, however, that while the investigations carried out by Patria and Erumban (2020) and Ganjoei et al. (2021) concern countries classified as low-income in our dataset, a subset of several low-income countries could yield different thresholds limits.

For low-income countries, we thus find our results of mobile and fixed telephone usage negatively impacting income inequality are supported by existing literature, and further that fixed broadband is yet to reach a level where it can have an appreciable impact. For individual internet usage and international bandwidth usage, we postulate that the inability to infer a direction of the impact is caused by the existence of a nonlinear relationship. Still, considering the significance of the negative impacts from mobile and fixed telephone usage, the analysis suggests that ICTs tend to decrease income inequality in low-income countries.

5.3 Synthesis of Discussion

By examining the total impact of ICTs on income inequality it has been found that three out of five ICT measures, namely mobile, internet, and fixed telephone usage, indicate a negative impact while international bandwidth usage indicates a positive impact, and the effect of fixed broadband usage is ambiguous. International bandwidth usage's impact as an ICT variable on income inequality is not previously studied, and it is difficult to say if a potential positive impact would outweigh the negative impact of the other three variables. The impact of international bandwidth usage is found to be smaller compared to mobile usage, internet usage and fixed telephone usage per unit, but the practicality of increasing the measures by one unit needs to be considered. In addition, our results regarding the measures of mobile usage, internet usage and fixed broadband usage can be related to several previous studies and backed by literature, which is not the case for international bandwidth usage. The evidence presented

supports the notion that ICTs have a negative impact on income inequality. However, it is important to note that the specific measure used can influence the magnitude of this impact. By considering the results presented in the literature in conjunction with our estimation results we therefore suggest that there's compelling evidence for a confirmation of hypothesis H1 and that ICTs alleviate income inequality on a global level.

We further analyzed and discussed the impact of ICTs on income inequality across income levels. In its entirety, the discussion indicates an overall negative impact of ICTs on income inequality across the three subsamples, thus supporting our findings on a global level and favoring a confirmation of hypothesis H1. Analyzing the results more closely has further revealed that the ICT variables with statistically significant impacts on income inequality are not identical across the subsamples, with the middle-income sample deviating from the otherwise consistent results obtained for the low- and high-income samples. Drawing on existing literature has facilitated an analysis and explanation of the observed differences by discussing, inter alia, the cost structure of the technologies, thresholds and saturation levels, and conditional effects such as political stability which suggests that the second hypothesis, H2, should be accepted.

5.4 Limitations

This study is subject to limitations that should be considered when interpreting the findings. Limitations originate from the data used, the regression model employed, and the selection of ICT measures, and recognizing these limitations is important for a comprehensive understanding of the research and to identify avenues for further investigation.

Firstly, the data used in this study may introduce limitations due to missing data and the exclusion of certain countries. The presence of missing data raises concerns regarding the representativeness of the sample and the potential for bias. Additionally, the removal of countries with incomplete data may disproportionately affect low-income countries, which was found to be the income group most affected by deletions in our dataset (see Table 4). This is further argued by Solt (2020), identifying that data from Africa and developing Asia exhibits higher uncertainty due to less complete data. This could potentially limit the generalizability of the findings, with one of the downsides of listwise deletion being the risks of potential sample bias in case data is not missing completely at random (Allison, 2001). Missing data is however not an unique feature for our study, argued by Allison (2001) as an issue everyone in statistical analysis faces sooner rather than later. In addition, several studies in this field use similar approaches to handle missing data (see Canh et al., 2020; Richmond & Triplett, 2018). It is thus important to acknowledge that the limitations of data for low-income countries may impact a comprehensive analysis of their unique circumstances, thus warranting caution when interpreting the results.

Secondly, the regression model employed in this study offers valuable insights but also has its limitations. One potential limitation lies in the selection of control variables, which may not capture the full complexity of the relationship between ICT and income inequality. Future research could explore the inclusion of more and different control variables that account for specific factors. However, as explained in Section 3.2, there is a trade-off between more complexity and goodness of fit which needs to be considered (Gujarati, 2022). Moreover, further testing of the model, particularly when applied to subsamples based on income groups, could improve the robustness of the model. In this study, only the Hausman specification test was conducted on the subsamples, and further use of specification tests are ways to potentially improve the specified model. Alternative regression techniques, such as nonlinear models and interaction terms, could also be considered to uncover potential nonlinear relationships and further examine the effect of control variables, examining the indirect effect in more detail.

Lastly, the ICT measures utilized in this study are limited to a few ICT measures, and do not cover the full spectrum of technological advancements. Notably, the exclusion of emerging technologies such as artificial intelligence (AI) may overlook their potential impact on income inequality. This is an aspect argued by Vu et al. (2020), where more creative and alternative measures of ICT are viewed as necessary to advance the understanding of ICT impact in future studies. Future research should therefore strive to incorporate these evolving ICT measures to gain a more comprehensive understanding of their influence and explore their interaction with traditional technologies. It should however be noted that sufficient time series data across countries on emerging ICTs, such as AI, is scarce and we therefore suggest further studies to be conducted as more data becomes available.

Acknowledging these limitations provides opportunities for further research to address these constraints and advance the understanding of the relationship between ICT and income inequality. Future studies could focus on expanding the available data, refining the regression model with more appropriate control variables and interaction terms, and incorporating a wider range of ICT measures including emerging technologies. By addressing these limitations, future research can contribute to a more nuanced and comprehensive understanding of the complex dynamics between ICT and income inequality.

6. Conclusion

In conclusion, this study aimed to extend the understanding of the relationship between ICTs and income inequality. By analyzing the impact of different ICT measures on income inequality globally and across country income levels, significant insights were developed. The findings of this study confirm the hypothesis that ICTs decrease income inequality on a global level. Specifically, three ICTs, namely mobile usage, internet usage, and fixed telephone usage, demonstrate an alleviating impact on income inequality. These results are consistent with existing literature and support the notion that ICTs have a favorable effect in reducing income disparities. However, the impact of fixed broadband usage remains ambiguous, and the potential worsening impact of international bandwidth usage on income inequality requires further investigation.

Moreover, the study examined the variation of ICT effects on income inequality across different income groups. In high-income countries, mobile and fixed telephone usage were found to have significant alleviating impacts on income inequality, while the impacts of fixed broadband and internet usage were less definitive. Our sample of middle-income countries exhibited a more complex relationship, where the cost structure of fixed broadband exacerbated income inequality but was counteracted by the inequality-reducing impact of fixed telephone and individual internet usage. In low-income countries, mobile and fixed telephone usage had notable alleviating impacts on income inequality and fixed broadband usage is yet to reach a level where it can have an appreciable impact. The impact of both internet usage and international bandwidth usage was inconclusive due to the potential existence of nonlinear relationships. The analysis reveals an overall alleviating impact of ICTs on income inequality across the three subsamples, thus supporting our findings on a global level and favoring a confirmation of hypothesis H1. However, the ICT variables with statistically significant impacts on income inequality differ across the subsamples. While the low- and high-income samples exhibit consistent results, the middle-income sample deviates from this pattern suggesting a confirmation of our second hypothesis.

This study contributes to the understanding of the complex dynamics between ICTs and income inequality. The evidence presented supports the notion that ICTs play a significant role in alleviating income inequality, which speaks for the importance of ICTs in reaching the tenth Sustainable Development Goal (SDG 10). However, the magnitude and direction of the impact identified can vary depending on the specific ICT measures and the income group under consideration. These findings underscore the importance of considering the specific ICT measures employed when assessing the impact on income inequality. Additionally, the findings may serve as a valuable resource for policymakers seeking insights into the role of ICTs in addressing income inequality. Lastly, the results highlight the need for further research to explore the potential of emerging technologies such as AI and their influence on income inequality. Thus, this study provides a foundation for future research endeavors aimed at

examining the relationship between ICTs and income inequality and exploring the implications for policy and socio-economic development.

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