STOCKHOLM SCHOOL OF ECONOMICS
Department of Economics
5350 Master's Thesis in Economics
Academic year 2018–2019

Equality Calling: The Relationship Between Mobile Broadband Expansion and Income Distribution Within Countries

Rowan Kurtz (41201)

Abstract:
Since its inception, information and communication technology has diffused at an incredible pace, to the point that the poorest quintile of the world's population is now more likely to have access to a mobile phone than to a toilet or clean water (World Bank, 2016). This paper examines if and to what extent the introduction and diffusion of mobile broadband technology affects income inequality within countries measured in terms of Gini coefficient, quintile income share, and the absolute income of each quintile. The study covers 69 countries for the 16-year period between 2002 to 2017. I find evidence that the initial introduction of mobile broadband is associated with a decrease in inequality while the expansion of mobile broadband has the opposite effect.

Keywords: Mobile Broadband, Inequality, ICT, Technology, Income, Gini Coefficient.

JEL: O10, 033

Supervisor: Martina Björkman Nyqvist
Date submitted: May 12, 2019
Date examined: May 24, 2019
Discussant: Jacopo Lunghi & Alexandra Beerkens
Examiner: Mark Sanctuary

Acknowledgements

Firstly, I would like to thank both my supervisors Martina Björkman Nyqvist and Harald Edquist for their invaluable guidance and feedback throughout this process. I would also like to express my gratitude to Ericsson for providing me the opportunity to write my thesis with their company and supporting my research. Additionally, I would like to thank Professor Ball and Professor Creedy for sharing their inequality data concerning New Zealand and The Conference Board for sharing data on ICT and non-ICT capital stock. Lastly, I would like to thank my family for their continued support and Jacopo Lunghi for all the insightful thesis discussions.

Contents

List of Figures

List of Tables

1. Introduction

Telecommunication technology has grown rapidly in recent decades. Globally, there are more than 5.6 billion unique mobile subscribers and 7.9 billion subscriptions, with those figures set to increase (Ericsson, 2019). Furthermore, thanks to advances in information and communication technology (ICT), the costs of telecommunication infrastructure and devices have decreased, making these goods affordable for consumers with limited purchasing power. Consequently, the poorest quintile of the world's population is more likely to have access to a mobile phone than to a toilet or clean water (World Bank, 2016).

As a result of this rapid diffusion, many economists have started examining the effects of ICT on society, finding a plethora of benefits including higher growth rates, more efficient markets, and higher productivity (Edquist et al., 2018; Jensen, 2007; Jorgenson et al., 2008; Oliner et al., 2000). Thus far, the research suggests that the diffusion of ICT has contributed to the recent global economic growth which has been responsible for increasing living standards across the globe[1].

While the benefits of technology for economic growth and productivity have been quantified, economists have also posited that technological innovation may be an important driver of income inequality (Acemoglu, 2000; Berman et al., 1994; Berman et al., 1997; Haskel et al., 1998; Jaumotte et al., 2013). Classic economic theory suggests that technological advances may be skill biased and could foster inequality. If ICT is skill biased, it will make high-skill workers more productive thereby exerting upwards pressure on their wages. Additionally, this higher level of productivity could increase the returns capital which would benefit the wealthy. This is then exacerbated by a depressed low-skill wage resulting from decreased demand for low-skill workers who lack the skills to participate in the new economy. Lastly, technological advances may crowd out low-skill workers as their jobs become automated. When considered in concert, the rising wages for high-skill workers, increasing returns to capital, higher unemployment for low-skill workers, and a decreased low-skill wage will result in greater levels of inequality.

[1] In 2015 only 9.9% of the world's population lived in extreme poverty compared to 26% twenty-five years earlier (Roser et al., 2019).

However, information and communication technology may diverge from previous economic theory. ICT has profoundly altered how information is spread and business is conducted; from increasing competition in markets that previously suffered from informational asymmetry (Jensen, 2007) to providing services to previously isolated populations (Jack et al., 2014), information and communication technologies have demonstrated the potential to improve economic and social outcomes for all levels of society.

Beyond the moral argument for addressing glaring economic disparities, understanding the drivers of inequality is imperative from a practical standpoint considering that research suggests that inequality has real effects on economic performance. Firstly, high-levels of inequality may hinder economic growth (Alesina et al., 1994; Galor et al., 1993) and, if left unattended, have the potential to foster social unrest and nationalistic policies (Solt, 2011). Given that inequality may adversely affect economic and political systems, identifying the relationship between ICT and inequality is integral to ensuring continued growth and stability.

While the majority of previous papers have examined the economic benefits due to expanded ICT services (Edquist et al., 2018, Czernich et al., 2011; Röller et al., 2001), the exact distribution of these benefits remains unquantified. In this paper, I attempt to answer the following questions:

- What effect does the introduction and expansion of mobile broadband have on the income distribution within countries?
- If there is an effect, which income quintiles are affected and how?
- How are absolute incomes affected?

To study these issues, I use a dataset containing 69 countries, of which 32 are OECD members, with data covering the 16-year period between 2002 and 2017.

This study makes several contributions to the current literature; firstly, it focuses on how ICT expansion, measured as the diffusion of mobile broadband, affects inequality. The majority of previous literature has focused on how the spread of ICT has affected growth and, besides

Edquist et al. (2018), have not used mobile broadband to measure ICT. As it becomes increasingly common throughout the world, understanding how mobile broadband specifically, rather than fixed high-speed connections (Hjort et al., 2018) or the share of ICT capital stock (International Monetary Fund's World Economic Outlook, 2007), affects income inequality becomes increasingly important. Secondly, to my knowledge, other studies have mainly used smaller samples of countries in earlier time periods which is likely to bias the results. This is exemplified clearly by Kuznets' findings (1955) which were largely influenced by his choice to consider a small set of countries in the early 20th century. By using a larger sample of countries over a 16-year period, this paper will provide more current and generalizable results than previous work.

My main findings are as follows; using a fixed-effects estimation, I find that the initial introduction of mobile broadband has an equalizing effect, decreasing a country's Gini coefficient by 2.4% on average. There is also evidence that the expansion of mobile broadband services may increase inequality, however this result is dependent on the specification. A deeper analysis using each quintile's income share suggests that the initial introduction of mobile broadband helps the lowest three quintiles at the expense of the top quintile while the expansion of mobile broadband decreases the third and fourth quintiles' income shares.

The rest of the paper is organized as follows. *Section 2* reviews the related literature concerning technology and inequality. *Section 3* provides the motivation and conceptual framework behind the paper. *Section 4* explains the methodology and the reasoning behind the model's specification. *Section 5* reviews the data and its sources. *Section 6* provides a brief, numerical overview of the variables used in the regressions, explores the empirical results, and attempts to identify how mobile broadband affects income inequality. *Section 7* provides multiple checks for robustness. *Section 8* discusses the paper's limitations, implications of the results, and suggestions for further research. *Section 9* concludes.

2. Related Literature

The benefits of ICT have been under debate since the invention of the technology. For example, although computers and phones became increasingly common in America in the late

20th century, economists were unable to identify their impact on productivity. This led to Robert Solow's (1987) famous remark on the computer productivity paradox, "you can see the computer age everywhere but in the productivity statistics." However, starting in the late 1990's, a productivity surge occurred which was largely attributed to ICT (Jorgenson et al., 2008). This sparked renewed enthusiasm for the potential of information and communication technologies to spur growth and improve economic outcomes.

Much of the existing research concerning the economic impacts of ICT has focused on quantifying its contributions to economic growth. In their paper, *How Important are Mobile Broadband Networks for Global Economic Development?*, Edquist et al. (2018) examine how the diffusion of mobile broadband technology affects GDP growth within countries. The authors demonstrate that the spread of mobile broadband services results in increased growth rates, although this effect fades with time. To identify this phenomenon, Edquist et al. (2018) utilize a non-linear instrumental variable approach based on the work of Griliches (1957) and Czernich et al. (2011). The authors conclude that a 10 percent increase in the adoption of mobile broadband results in a 0.8 percent increase in GDP growth which, considered at a global scale, would account for approximately 600 billion USD in 2016.

These results are supported by Röller et al. (2001) who find a significant positive causal link between telecommunications infrastructure and economic development in OECD countries. In their paper, the authors find that a percent increase in the penetration of telecommunication infrastructure (defined as mainlines per capita) results in a 0.15% increase in the annual growth rate. Waverman et al. (2005) find similar results for developing countries as well.

The introduction of ICT may also affect economic outcomes by ameliorating information asymmetries, promoting access to financial services, and improving social outcomes. To examine how ICT may solve informational asymmetries, Jensen (2007) studies the effect that cellphone adoption had on Kerala's local fishing industry. The author utilizes the introduction of mobile phone service in Kerala during the 1990's to identify the effect cellphone adoption has on prices, waste, and surplus. The establishment of mobile phone service in the region was staggered and enables Jensen to utilize a difference-in-difference approach. Comparing pre-coverage to postcoverage outcomes to estimate the economic effects of cellular coverage, Jensen finds that mobile phone coverage decreased price dispersion by approximately 40% (5 rupees per kilogram), effectively eliminated waste, and improved both consumer and producer surplus by increasing monthly revenues by 9% and lowering the average price per kilo by 5%.

An additional benefit of improved cell phone access is the strengthening of social safety nets. Jack et al. (2014) utilize the M-PESA program in Kenya, which allows participants to send money via mobile phone for a nominal fee, to examine the benefits households derive from risk sharing. They test the hypothesis that, due to lower transaction costs, "mobile money" programs will result with an increased flow of remittances and, in turn, stabilize consumption in face of negative, exogenous shocks (e.g. drought, illness, etc.). The authors' findings show that M-PESA program participants send more remittances than non-participants and, as a result, enjoy smoother consumption in the face of negative, exogenous shocks.

While there exists a large body of research concerning how ICT affects growth and the positive externalities associated with the diffusion of such technology, exactly how these benefits are distributed across societies is still a topic of debate.

Economic theory suggests technological change may be skill biased and could exacerbate existing economic inequalities (Acemoglu, 2000; Akerman et al., 2015; Autor, 2014; Berman et al., 1994; Berman et al., 1997; Haskel et al., 1998). Examining the decrease in the demand for unskilled workers in the American manufacturing industry in the 1980's, Berman et al. (1994) find that technological progress is strongly correlated with demand for more highly skilled workers. This finding was corroborated by Berman et al. (1997) who examine the demand for high and low-skill workers in OECD countries. These shifts in labor demand towards high-skill workers result in elevated wages for high-skill employees and depressed wages for low-skill workers, thereby fostering economic inequality. Furthermore, new technologies may not only decrease the wages of low-skill workers, but ultimately may take their jobs as well.

These findings have been supported by empirical studies as well. In their paper *The Skill Complementarity of Broadband Internet*, Akerman et al. (2015) utilize the expansion of broadband access points and firm-level data from Norway to identify whether broadband internet is skill biased. The authors find evidence suggesting that the introduction of broadband improves outcomes for skilled workers and worsens outcomes for low-skill workers which supports the theory that advances in ICT are skill biased

Additionally, in their paper, *Rising Income Inequality: Technology, or Trade and Financial Globalization?*, Jaumotte et al. (2013) examine the relationship between globalization, technological progress and income inequality. Using panel data from the late 20th century, the authors find that the spread of ICT, measured as the share of ICT capital stock of the total capital stock, is a major driver of the growing income inequality observed in their sample. More specifically, when the authors decomposed the aggregate increases in the Gini coefficient, technology was responsible for 0.74 percent of the annual average increase whereas globalization contributed 0.08 percent.

Jaumotte et al.'s findings are backed by previous research conducted by the IMF's World Economic Outlook (2007) in which the IMF notes the trend of increasing within-country inequality in the late 20th century and identified technology growth as a main driver of the increased economic disparity. The paper also uses the percent of the total capital stock which is ICT capital stock as the independent variable and Gini scores and income quintiles as dependent variables. The study finds that technological progress explained the majority of the 0.45 percent average annual increase in the Gini coefficient observed in their sample with trade and financial deepening each contributing approximately 0.1 percent per year.

While these studies paint a rather bleak picture with regards to technology's effect on inequality, other papers have identified possible equalizing effects of ICT. In their paper examining how fast internet affects employment in Africa, Hjort et al. (2018) identify positive effects of increased ICT infrastructure. In their study, Hjort et al. attempt to estimate the economic benefit of connecting urban areas to the intercontinental high-speed grid. They use the sequential linkage of urban areas in Sub-Saharan Africa to internet submarine cables to estimate the effect high-speed internet access has on unemployment, job inequality, and firm productivity. Their analysis identifies significant effects on all three outcome variables. First, internet linkage increased probability that an individual is employed by between 3.3 and 13.2 percent, depending on location. Further, the evidence suggests firm productivity rose and that improved internet access augmented the number of new companies entering the market, particularly in the finance and service sectors. Lastly, the authors find no evidence of increased job inequality. Rather, access to high-speed internet "appears to shift employment shares towards higher-productivity occupations", suggesting that the share of high-skilled job opportunities grew while the number lower-skill jobs remained static, thereby increasing employment for the entire population regardless of educational attainment. While this does not necessarily contradict the IMF's findings, it does suggest that ICT growth can benefit both skilled and unskilled workers.

3. Motivation and Conceptual Framework

This paper is motivated by the fact that the majority of previous literature examining the economic impact of ICT is focused on economic growth. However, it is important to remember that growth is a means to an end rather than the end itself and that it is only as valuable as far as it benefits society. Accordingly, acknowledging previous researchers' findings that ICT diffusion aids growth (Edquist et al., 2018; Röller et al., 2001, Waverman et al., 2005), this paper attempts to qualify these results by identifying how these benefits are distributed within societies.

The driving theory behind the supposition that ICT may affect inequality is the concept that technological progress can be skill biased (Acemoglu, 2000; Autor, 2014; Berman et al., 1994; Berman et al., 1997; Haskel et al., 1998). As mentioned previously in *Section 2*, if ICT is a skill biased technology, demand for higher-skilled workers will grow as it is integrated into the economy which will, in turn, increase the high-skill wage. Conversely, demand for low-skill workers fall, which exerts downwards pressure on the low-skill wage. Additionally, low-skill workers may face higher levels of unemployment as routine jobs are automated. This wage divergence combined with the possibility of higher unemployment for low-skill workers will likely result in higher levels of inequality.

4. Methodology

4.1 Main Econometric Specification

I base my model on two previous empirical specifications, combining frameworks from Jaumotte et al.'s (2013) and Edquist et al.'s (2018) studies. The equations are as follows:

$$ln(Gini)_{it} = \beta_0 + \beta(Introduction)_{it} + \delta(controls)_{it} + \eta_i + \theta_t + \epsilon_{it} \tag{1}$$

Where the dependent variable, $\ln(Gini)_{it}$, is the natural log of the Gini coefficient in country *i* at time *t*, β_0 is a constant, *Introduction* is a dummy variable representing whether mobile broadband has been introduced in country *i* at time *t*, and β represents the percent change in the Gini coefficient that occurs as a result of the introduction of mobile broadband[2]. δ represents how the control variables affect a country's Gini coefficient in country *i* at time *t*. My controls were selected based on prior cross-country research examining inequality and its determinants (Jaumotte et al., 2013) and include a country's level of economic development, education, financial development and integration, democratic governance, inflation, capital stock, unemployment, openness to trade, natural resource dependence, workforce characteristics, and population size. Justifications and explanations for the variables chosen are provided below in *Section 4.3.2*. The model also includes country- fixed effects, η_i, and time-fixed effects, θ_t. Country-fixed effects are utilized in the regression to control for unobserved, country-specific factors which could contribute to changes in inequality. Using the Hausmann test, I reject the null hypothesis that the random-effects model is the correct specification[3], thereby supporting my inclusion of country fixed-effects**.** Lastly, ϵ_{it} is the error term. The error terms are clustered at the country level. This is based on the assumption that the variation in the model is not random across the sample and that errors are likely to be correlated at the country level.

In my second specification, both the penetration level and introduction are included to account for the possibility that mobile broadband may affect income inequality both through its introduction and expansion. For example, the introduction of mobile broadband could decrease

[2] Unless stated otherwise, the introduction of mobile broadband is defined as when 1% of total mobile devices are broadband capable.
[3] Conducting the Hausman test results in a χ^2 of 91.38 which allows up reject the null hypothesis that the correct specification is a random-effects model. Consequently, I continue with a fixed-effects specification.

inequality considering that the construction of such networks is expensive and the spending necessary to install new mobile broadband networks may stimulate the economy and decrease unemployment. However, if a critical mass of users is necessary for the benefits of a technology to materialize (Röller et al., 2003), then simply examining the introduction of mobile broadband would fail to identify mobile broadband's true effect. As such, I also include the penetration rate in my regression to identify how increases in mobile broadband penetration alter the income distribution within a country. The model is shown below:

$$ln(Gini)_{it} = \beta_0 + \alpha(Expansion)_{it} + \beta(Introduction)_{it} + \delta(controls)_{it} + \eta_i + \theta_t + \epsilon_{it} \qquad (2)$$

Where the variables are defined as in *Equation 1* except that *Expansion* is defined as the percentage of mobile devices which have mobile broadband capabilities in country *i* at time *t* and α is the percent change in the Gini coefficient due to a percentage point increase in the expansion of mobile broadband.

In addition to examining how the introduction of mobile broadband affects inequality within a country, this paper will briefly attempt to identify how each quintile's income share is impacted. The specification is shown below and uses the same controls as listed above.

$$IncomeShare_{jit} = \beta_0 + \alpha(Expansion)_{jit} + \beta(Intro)_{jit} + \delta(controls)_{jit} + \eta_i + \theta_t + \epsilon_{jit} \quad (3)$$

Where $IncomeShare_{jit}$ is the share of total income controlled by quintile *j* in country *i* at time *t*. All other variables are defined as they are in *Equation 2* although $Introduction$ has been shortened to $Intro$.

Lastly, I attempt to determine how each quintile's absolute income is affected by the expansion and introduction of mobile broadband. Due to a lack of information, the average income for quintile *j* is calculated using the IMF's approach (2007) which relies on data concerning GDP per capita and income distribution. The calculation is shown below:

$$\frac{Y_{jt}}{Pop_{jt}} = \left(\frac{Y_{jt}}{Y_t}\right)\left(\frac{Y_t}{Pop_t}\right)\left(\frac{1}{0.2}\right) \; where \; j \in [1,5] \qquad (4)$$

Where Y_{jt} is the total income of quintile *j* at time *t*, Pop_{jt} is the population of quintile *j* at time *t*, Pop_t is the total population at time *t* and Y_t is the GDP at time *t*. The regression specification is shown below.

$$AvgInc_{jit} = \beta_0 + \alpha(Expansion)_{jit} + \beta(Introduction)_{jit} + \delta(controls)_{jit} + \eta_i + \theta_t + \epsilon_{jit} \quad (5)$$

Where $AvgInc_{jit}$ is the average income for quintile *j* in country *i* at time *t*. All other variables are defined as they are in *Equation 2*.

4.2 Instrumental Variable Specification

After the initial regressions, the model is verified using an instrumental variable approach. A linear IV specification is reported in *Section 7.3* while a non-linear approach commonly used in previous literature (Czernich et al., 2011; Edquist et al., 2018) is reported in *Appendix A*. I use an instrumental variable approach to address the possibility of simultaneity between inequality and the diffusion of mobile broadband. While I will argue the validity of the IV in *Section 7.3*, the first and second-stage equations are depicted below.

First stage:

$$(\widehat{M})_{it} = \Upsilon(FixedPhone)_{i(t-20)} + \delta(controls)_{it} + \eta_i + \theta_t + \mathrm{v}_{\mathrm{it}} \quad (6)$$

Where FixedPhone is the number of fixed phone subscriptions per capita in country *i* at time *t-20*, $\widehat{M}$ is the predicted percentage of mobile devices which have mobile broadband capabilities in country *i* at time *t*, and v_{it} is the error term. The remaining variables are defined as they were previously. I replace the actual expansion of mobile broadband with the predicted values, $\widehat{M}$, yielding the second-stage equation:

$$ln(Gini)_{it} = \alpha_{IV}\left(\widehat{M}\right)_{it} + \delta(controls)_{it} + \eta_i + \theta_t + \epsilon_{it} \quad (7)$$

If correctly identified, α_{IV} is an unbiased estimator of mobile broadband's effect on income inequality. I do not include an instrument for the introduction of mobile broadband considering that it is a binary variable which would require a non-linear first stage to model.

4.3 Regression Variables

4.3.1 Dependent Variables

4.3.1.1 Natural Log of the Gini Coefficient

My first dependent variable is the natural log of the Gini coefficient. The Gini coefficient ranges from zero, representing a perfectly equal society, to one, a perfectly unequal society. However, the realistic range of Gini coefficients is between 0.20 and 0.65 (IMF 2007). I include measures calculated using both income and consumption data and transform them using the natural log given that absolute changes in Gini coefficients are relatively hard to conceptualize. By using the natural log of the Gini coefficient, the effect is measured as a percentage change which, although still relatively difficult to comprehend, eases the interpretation slightly.

Figure 1 – Gini Coefficients Over Time

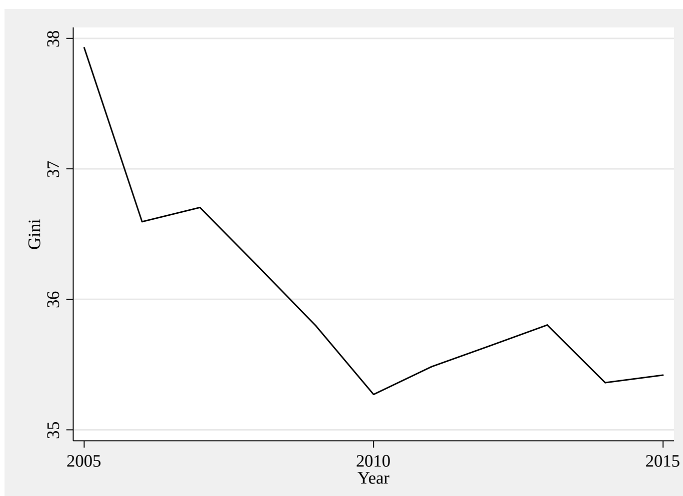

Figure 1 – Evolution of Gini coefficients for the 69 countries in my sample between 2005 and 2015. Source: Author's rendering using data from the United Nation's World Income Inequality Database (2018)

The evolution of the Gini coefficient for countries in my sample is illustrated above in *Figure 1*. In the early 21st century, the average Gini for my sample has decreased from approximately 0.38 to 0.35, which is roughly equivalent to the difference in inequality between Russia and Italy[4].

[44] Using 2015 data.

However, examining *Figure 7* in *Appendix D* reveals that this trend is largely influenced by falling inequality in Latin America. Conversely, inequality has either risen or remained stable for the majority of countries in Europe and North America. A brief explanation of how the Gini coefficient is calculated is presented in *Appendix E.*

4.3.1.2 Quintile Income Share

My second dependent variable is quintile income share. As previously stated, the Gini coefficient is difficult to interpret in isolation. As such, I include quintile income share which enables me to identify the underlying changes that drive the overall shifts in the Gini coefficient. *Figure 2* depicts how each quintile's income share has evolved over time. As shown below, the top quintile has experienced a minor decrease but still controls an income share approximately six times that of the lowest quintile.

Figure 2– Average Share of Income by Quintile

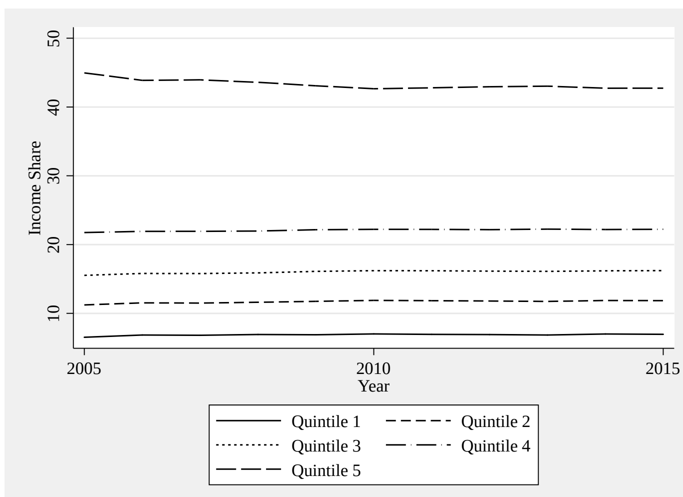

Figure 2 – The evolution of the average income share by quintile from 2005 to 2015. Source: Author's rendering using data from the United Nation's World Income Inequality Database (2018).

4.3.1.3 Absolute Income by Quintile

My final dependent variable is the absolute income of each quintile. Similar to the relationship between quintile income share and the Gini coefficient, examining the absolute income provides further nuance for shifts in quintile income share. For example, if the top quintile's average income is increasing more rapidly than the lowest quintile's income, it would be possible for the lowest quintile to see its income share fall despite an increase in its absolute income. As stated previously, due to a lack of data this variable was calculated using income shares and GDP per capita and, as such, is an estimation. *Figure 3* details the average absolute income of each quintile between 2005 and 2015. As shown below, incomes have risen for all quintiles. However, the gains do not appear to be equitably distributed with the top quintile experiencing larger income growth than the lower quintiles.

Figure 3– Average Absolute Income by Quintile

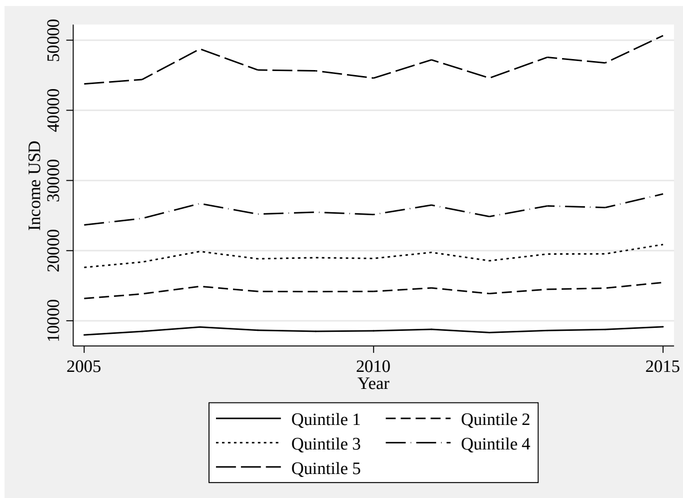

Figure 3 – The evolution of the absolute income by quintile from 2005 to 2015. Source: Author's rendering using data from the United Nation's World Income Inequality Database (2018).

4.3.2 Independent Variables

4.3.2.1 Penetration Rate and Introduction of Mobile Broadband

The penetration of mobile broadband is measured as the percentage of total connections which are broadband capable – where broadband capable is defined as devices with a download speed of 256 kB/s or higher. This includes both contracts and prepaid subscriptions for all device types. It is also worth noting that connections differ from subscribers in that a single user may have multiple connections. I do not use the log of mobile broadband penetration considering it further complicates the interpretation of the results. In this paper, I define the introduction of mobile broadband as 1% penetration rate. As a check for robustness, I also include a 5% threshold. The first country in my sample to reach the 1% penetration rate threshold was South Korea in 2003 which was then followed by Austria, Denmark, Italy, Luxembourg, Sweden, and the United Kingdom in 2004. The last country in the sample to pass the 1% threshold for mobile broadband penetration was Pakistan in 2014.

Over the past sixteen years, mobile broadband connections have been increasing rapidly throughout the world. Below, *Figure 4* illustrates mobile broadband's diffusion in my sample. In addition to highlighting the speed at which mobile broadband technology spreads, the graph suggests that the diffusion process may be a non-linear process.

Figure 4 – Expansion of Mobile Broadband

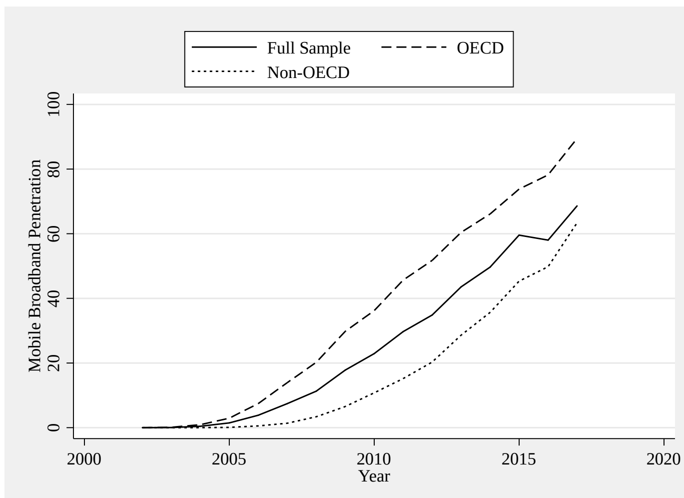

Figure 4 – The expansion of mobile broadband by country. Source: Author's rendering using data from the GSMA Wireless Intelligence Database (2018).

4.3.2.2 GDP Per Capita

GDP per capita, measured in constant 2010 USD, is included as a control to account for the possibility that a country's level of economic development may affect its level of inequality. Simon Kuznets theorized that the evolution of inequality may follow an "inverted U" shape in which inequality rises as low-income countries develop, peaks, and then declines as they transition towards higher standards of living (Kuznets 1955). However, while early research supported this theory (Matins-Bekat et al., 2009; Paukert, 1973), others have failed to find evidence of the Kuznets Curve (Anand et al., 1993; Deininger et al., 1998; Ravallion, 2001). Although the empirical research is inconclusive, the possibility that a country's level of wealth affects inequality is controlled for using GDP per capita

4.3.2.3 Education Level

A country's level of education has the potential to affect inequality both directly and indirectly as it relates to technology and are controlled for using the mean years of schooling for persons age 15 and above (United Nations Development Programme, 2017).

Directly, education may affect inequality if there is a large discrepancy in the quality or amount of education received by different groups within a country. In his paper, *Schooling and Income Distribution: Evidence from International Data,* Winegarden (1979) finds that, although increases in the average amount of education may have an equalizing effect, differences in educational attainment are an important determinant of income disparities.

In addition to its direct effects on income inequality, education could affect the income distribution indirectly through its interaction with technology. Technological advances may favor high-skilled workers by increasing their productivity. Given that the skill level of workers is likely linked to education and training, the introduction of technologies into a society with low-education levels or a large education gap could result in increased inequality as the wages of skilled laborers with more education increase and the wages of uneducated workers simultaneously fall (Berman et al., 1997). Conversely, evenly distributed increases in education could help close the gap as low-wage workers grow their skills and begin to earn high-skill wages. *Figure 6* in the appendix illustrates the evolution of the average education level and Gini Coefficient throughout the early 21^{st} century. As shown, the average years of schooling is increasing for most countries in my sample, but the graphs do not readily suggest a connection between education and inequality.

Unfortunately, using the mean years of schooling for persons age 15 and above fails to provide a description as to how educational attainment or the quality of education is distributed across a country's population and, as such, fails to provide a more nuanced explanation of education's relation to inequality.

4.3.2.4 Financial Openness and Integration

A large body of work has examined the financial sector's effect on income inequality, with many researchers finding that global financial integration tends to exacerbate income differentials (Jaumotte et al., 2013; Wahid et al., 2012). While there are many of possible indicators for financial openness and integration, I use the net inflows of foreign direct investment (FDI) and the amount of domestic credit provided by the financial sector.

Net inflows of FDI – measured as a percentage of GDP – is chosen as a control considering that it is likely to be highly correlated with other indicators of global financial integration. Additionally, in their paper examining the effects of technology and globalization on inequality, Jaumotte et al. (2013) find that the only statistically significant financial indicator from the Chinn-Ito Index was the "ratio of inward FDI stock to GDP".

Similarly, the amount of credit provided by the financial sector – measured as a percentage of GDP – is used to account for the maturity and importance of local financial institutions. In their paper, Wahid et al. (2012) find that the development of the financial sector, defined as the credit to the private sector, is associated with an increase in income inequality.

4.3.2.5 Trade

Similar to financial integration, a country's openness to trade may affect how income is distributed within the society. However, the literature concerning the relationship between trade and income inequality is inconclusive with some authors identifying a positive relationship (Wahid et al., 2012) and others an equalizing effect (Jaumotte et al., 2013). To further complicate the matter, the Stolper-Samuelson model, derived from the classic Heckscher-Ohlin model, suggests there may be heterogenous effects for countries (Stolper et al., 1941). For example, in a two-country model where a developed country is trading with developing economy, the developing economy will likely have a large pool of cheap labor giving it a comparative advantage in producing and exporting labor-intensive products. This will result in the low-skill jobs migrating from the high-income to the low-income country which will increase the low-skill wage in the developing economy. Consequently, inequality in the developing country will decrease and vice versa in the developed country. While the Stolper-Samuelson model has been challenged and indeed oversimplifies the dynamic nature of international trade, it serves to highlight the need to account for a country's openness to trade when considering inequality. As such, I include trade measured as a percentage of GDP as a control in my model.

4.3.2.6 Structure of the Economy

The structure of a country's economy may also have ramifications for the society's level of inequality. For example, countries rich with natural resources may suffer from a higher level of inequality given that resource extraction tends to be a capital-intensive process which may favor high-skilled workers and those with access to capital. Marchand et al. (2015) discover evidence of this while examining the effect of the energy boom in Western Canada on inequality. The authors find that, although the increased economic activity raised incomes overall, the energy sector's growth resulted in higher levels of inequality. Similarly, an economy which is overly dependent on low-skill industries such as agriculture may suffer from higher levels of economic inequality when technology is introduced, particularly if these low-skilled workers are unable to access the higher paying jobs created by technology adoption. As such, I include natural resource rents measured as a percentage of GDP and the percentage of the total workforce employed in agriculture as controls.

4.3.2.7 Capital Controls

The amount of capital in a society could also impact a country's level of inequality. Larrain (2015) suggests that higher levels of capital may foster inequality as a result of capital favoring higher-skill workers. This results with higher demand for high-skill workers, increasing their wages and, in turn, inequality. I control for the non-ICT capital stock per capita within a country – measured in millions of 2018 PPP adjusted USD.

4.3.2.8 Government Structure and Spending

The political structure of a society is also likely to affect the country's level of inequality. To account for this effect, I use the Center for Systemic Peace's Polity IV dataset (2018) and Ulfelder et al.'s (2012) democracy dataset to create a dummy variable for democratic governance. However, how a democratic government affects a country's income distribution is not obvious. Democratic institutions could provide a voice for low-income individuals to advocate for progressive social policies and the redistribution of wealth. Conversely, it could also result in "elite capture" which would allow for the top earners in society to protect their status (Acemoglu et al, 2008). Additionally, given that many governments implement job-creation and anti-poverty programs, government spending is likely to affect income inequality within countries. Gafar et al. (2005) find that government spending has heterogenous effects with public spending on basic services benefitting the poor while more advanced infrastructure and projects benefit the rich. As such, I also control for government expenditures as a percentage of GDP

4.3.2.9 Inflation

I also include inflation, measured as the annual percentage increase in consumer prices, as a control. The literature concerning inflation's effect on income distribution is inconclusive. Examining inequality in Korea, Yue et al. (2011) failed to find a conclusive link between inflation and income distribution. Conversely, in his IMF study, Bulíř (2001) finds a correlation between inflation levels and the Gini coefficient. There are several possible explanations for the lack of consensus concerning inflation's relationship with income inequality; first, different levels of inflation may have heterogenous effects on the distribution of income – e.g. hyperinflation may not impact incomes similarly to other inflation levels. Moreover, inflation levels may be associated with other economic factors such as monetary policy, macroeconomic conditions, and fiscal policy which could impact inequality. Lastly, if wages are able to adjust faster to inflation than the return on capital, then inflation would likely decrease the upper quintiles' income shares.

4.3.2.10 Population

The population of a country may affect its level of inequality through various channels. Campante et al. (2007) suggest that more populous countries tend to be more equal. The authors argue that a larger population is more easily able to oust the ruling elite and demand more benefits. Another possible channel through which population may affect inequality is population growth. If economic growth is outpaced by growth in the population, inequality will likely increase (Mugisha et al., 2017). To account for this, I include the size of the population as a control.

4.3.2.11 Unemployment

The level of unemployment within a society is likely to have a significant impact on a society's level of income inequality. As inequality increases, a larger portion of the population will not be earning an income, thereby decreasing the lowest quintiles' average income shares and, in turn, increasing the Gini coefficient. Additionally, higher levels of unemployment for low-skill workers may exert downwards pressure on the low-skill wage (Glyn, 1995). Consequently, I use the unemployment rate as a control.

5. Data

The data utilized in this paper has been gathered from multiple sources. Data concerning countries' Gini coefficients and income distribution is from the United Nation's World Income Inequality Database (WIID) which consolidated data from previous surveys and studies into one database (2018). For consistency, whenever possible, the Gini Coefficient data was collected from the World Bank's PovCal surveys and was calculated using per capita, net income measured at the household level. I choose this measure because it was the most common measure available across countries. While income data was available for the majority of OECD countries and Latin American countries, a handful of nations only reported consumption-based Gini coefficients. This decreases the cross-country comparability of the coefficients. However, given that the purpose of this paper is to identify intra-country changes in economic inequality, countries using consumption-based coefficients are included in the sample. It is possible that consumption-based Gini coefficients will be less sensitive to changes given consumers propensity to smooth consumption. This concept will be further explored in *Section 7.1.2.* Lastly, given that surveys regarding consumption and income are not necessarily conducted annually, the panel is unbalanced.

I exclude countries for which there is less than eight years for which the Gini coefficient was calculated. As such, each country in the sample has data points for at least half of the 16 possible years. There is consistent data, defined as eight or more years of data between 2002 and 2017, for 69 countries. *Table 1* lists the countries in the regression sorted by OECD membership status.

Data for the penetration rate of mobile broadband is from the GSMA Wireless Intelligence Database (2018) and covers from 2002 to 2017.

Data concerning the total capital stock and the ICT capital stock within countries is from the Conference Board's Total Economy Database (2019).

Education data is from the Database United Nations Development Programme's Human Development Report (2017).

Data concerning GDP per capita, FDI inflows, the domestic credit provided by the financial sector, trade, natural resource rents, employment in agriculture, government expenditure, and inflation rates are all from the World Bank DataBank (2017).

Lastly, the data regarding democratic governance was gathered from the Center for Systemic Peace's Polity IV (2018) and Ulfelder et al.'s (2012) democracy datasets.

Table 1 – OECD and Non-OECD Countries Included in the Regression

OECD Countries
Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Korea, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, Norway, Poland. Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom, and the United States.
Non-OECD Countries
Argentina, Armenia, Belarus, Bolivia, Brazil, Bulgaria, China, Colombia, Costa Rica, Croatia, Cyprus, Dominican Republic, Ecuador, El Salvador, Georgia, Honduras, Indonesia, Jamaica, Kazakhstan, Kyrgystan, Macedonia, Malta, Moldova, Montenegro, Pakistan, Panama, Paraguay, Peru, Philippines, Romania, Russia, Serbia, Thailand, Ukraine, Uruguay, Venezuela, and Vietnam.

Source: Author's rendering using data from the OECD 2018.

6. Results

6.1 Descriptive Statistics

Table 2 displays selected descriptive statistics for variables used in the regressions. For the full table, see *Table 14* in *Appendix C*.

Table 2 – Descriptive Statistics

Variable	Mean	Std. Dev.	Min.	Max.	Obs.
Gini Coefficient	0.4	0.1	0.2	0.6	908
Bottom Quintile's Income Share	6.8	2.1	1.6	10.4	867
Top Quintile's Income Share	43.8	7.1	33.1	63	867
Mobile Broadband Penetration	23.1	26	0	99.5	908
Year of Introduction	2007	2.1	2003	2014	69
GDP Per Capita	21,290.7	22,186.6	676.3	111,968.3	908
Trade	92.4	51.8	22.1	410.2	907
Net Inflow of FDI	7	24.4	-58.3	451.7	908
Non-ICT Capital (Billions USD)	4,064.2	9,916.9	25.7	80,000	837
Domestic Credit Provided by Financial Sector	92.1	64.9	5.5	316.6	876
Inflation Rate	5.1	6.9	-4.5	81.1	900
Share of Population Employed in Agriculture	14.8	13.3	0.5	62	908
Total Natural Resource Rent	3	4.8	0	32.4	898
Mean Years of Schooling	10.2	2.2	3.8	14.1	908
Government Spending	17	4.3	5.5	30	907
Unemployment Rate	8.1	4.8	0.4	32	908

As shown above, there is substantial variation in the Gini coefficient which ranges from 0.23 to 0.6. As suggested by *Figure 1*, the max Gini decreases from 0.6 to 0.5 from the first to last observation suggesting that highly unequal countries are becoming more equitable. There is a large difference between the share of income controlled by the top and bottom quintiles with the top income quintile controlling over six times the income of the lowest quintile on average. Lastly, although mobile broadband was, on average, introduced in 2007, there still exists a large digital divide; in 2016 South Korea had a penetration rate of 99% whereas Kyrgyzstan had 22%.

6.2 The Effect of Mobile Broadband on the Gini Coefficient

Table 3 and *Table 4* provide the initial results for the introduction and expansion of mobile broadband respectively. Due to a lack of data, five countries are dropped from the regressions that use controls: El Salvador, Honduras, Montenegro, Panama, Paraguay. In *Table 3* the first two columns contain the coefficients obtained using a pooled regression model. The coefficients in the last four columns are estimated using a fixed-effects specification. The results show that for the 1% penetration threshold, regardless of specification, there is a negative and statistically significant association between the introduction of mobile broadband penetration and a country's Gini coefficient. The fourth column suggests that the introduction of mobile broadband results in a 2.7% decrease in a country's Gini coefficient.

Table 3 - The Effect of the Introduction of Mobile Broadband on Gini Coefficients

Variables	Dependent Variable: Log Gini					
Introduction	-0.040***		-0.038***		-0.027***	
	(0.009)		(0.009)		(0.010)	
Introduction (5% Threshold)		-0.006		-0.005		0.002
		(0.008)		(0.008)		(0.009)
Employment in Agriculture					0.003*	0.003*
					(0.002)	(0.002)
FDI Net Inflows					0.000	-0.000
					(0.000)	(0.000)
Trade					0.001*	0.001**
					(0.000)	(0.000)
Inflation					-0.001	-0.001
					(0.000)	(0.000)
GDP Per Capita					0.000	0.000
					(0.000)	(0.000)
Domestic Credit Provided by Fin. Sector					0.000	0.000
					(0.000)	(0.000)
Mean Years of Schooling					0.010	0.008
					(0.011)	(0.011)
Natural Resource Rents					-0.000	0.000
					(0.002)	(0.002)
Democracy					-0.019	-0.022
					(0.021)	(0.024)
Government Expenditure					0.001	-0.000
					(0.003)	(0.003)
Non-ICT Capital					1.435	1.582
					(0.962)	(0.967)
Population					0.000*	0.000*
					(0.000)	(0.000)
Unemployment Rate					0.006***	0.006***
					(0.002)	(0.002)
Constant	3.616***	3.614***	3.622***	3.622***	3.035***	3.073***

	(0.030)	(0.030)	(0.011)	(0.011)	(0.143)	(0.146)
Observations	908	908	908	908	793	793
R-squared			0.171	0.174	0.311	0.297
Number of Countries	69	69	69	69	64	64
Country Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: Errors are clustered at the country level.

Interestingly, the 5% threshold has no statistical significance. These results indicate that the equalizing effects within a country due to the introduction of mobile broadband occur in the early stages of network expansion. This could possibly result from increased demand for labor as companies and governments construct the network. Additionally, the increased spending could have a multiplier effect throughout the rest of the economy, thereby stimulating employment and wages in other sectors. Unfortunately, I do not have the necessary data to identify the channel through which the introduction of mobile broadband decreases income inequality.

In *Table 4,* I examine the impact that the expansion of mobile broadband has on the Gini coefficient. The results show no statistically significant relationship between the expansion of mobile broadband and a country's Gini coefficient when control variables are included. As in *Table 3*, the introduction of mobile broadband, defined as 1% penetration rate, is associated with a decline in a country's Gini coefficient. These findings highlight the importance of the introduction of mobile broadband with regards to income inequality within a country. As such, understanding whether this is due direct or indirect employment creation or another factor is critical to ensuring that countries are able to maximize the equalizing effect derived from expanding ICT services.

The share of the population that is employed in agriculture has a positive, significant association with the Gini coefficient. This likely due to the low-wage nature of agriculture work; as the share of the population is employed in low-skilled work increases, the lower quintiles' income shares are likely to decrease, and inequality will rise.

Trade is also positively correlated with higher inequality. This could be partially explained by Dinopoulos et al.'s (1999) work which suggests trade liberalization raises firms' incentive to innovate which, in turn, increases the wages for high-skilled workers in comparison to low-skill workers. Another possible explanation was posited by Egger et al. (2009) who suggest that the heterogenous nature of firms and labor market frictions, combined with international trade, may result with increasing inequality. In their model, as trade increases, domestic firms come under increasing pressure from foreign firms and, as a result, low productivity firms fail. This results in increased market shares for highly productive firms and, in turn, higher wages for productive employees. The combination of low-productivity workers being laid off and increased wages for highly productive workers would contribute to higher levels of inequality. However, identifying exactly how trade liberalization affects inequality is beyond the scope of this paper.

Inflation has a significant and negative relationship with Gini coefficients. While interesting, this result is difficult to interpret given that different levels are likely to have heterogenous effects on inequality. The relationship between low, healthy levels of inflation and increased demand for labor provide a theoretical explanation for why inflation is negatively associated with inequality.

Lastly, both the size of a country's population and the unemployment level have a positive and significant relationship with inequality. While the channel through which population affects inequality is not obvious, unemployment is relatively intuitive. As unemployment rises, a larger portion of the population is without income, thereby decreasing the lower quintiles income share and increasing inequality. The rest of the control variables are not significant.

Table 4 - Regressions Concerning Mobile Broadband's Effect on Gini Coefficients

Variables	Dependent Variable: Log Gini		
Mobile Broadband Connections	0.002***	0.001***	0.000
	(0.000)	(0.000)	(0.000)
Introduction		-0.023***	-0.024***
		(0.008)	(0.009)
Employment in Agriculture			0.003*
			(0.002)
FDI Net Inflows			0.000
			(0.000)
Trade			0.001*
			(0.000)
Inflation			-0.001*
			(0.000)

GDP Per Capita			0.000
			(0.000)
Domestic Credit Provided by the Financial Sector			0.000
			(0.000)
Mean Years of Schooling			0.010
			(0.011)
Natural Resource Rents			-0.000
			(0.002)
Democracy			-0.017
			(0.021)
Government Expenditure			0.000
			(0.003)
Non-ICT Capital			1.143
			(1.031)
Population			0.000*
			(0.000)
Unemployment Rate			0.005***
			(0.002)
Constant	3.605***	3.614***	3.081***
	(0.030)	(0.010)	(0.151)
Observations	908	908	793
R-squared		0.227	0.314
Number of Countries	69	69	64
Country Fixed Effects	No	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: Errors are clustered at the country level.

6.3 Income Share

Table 5 provides a deeper insight into the underlying changes experienced by each income quintile that contribute to overall shifts in the Gini coefficient. Due to a lack of data for quintile income shares and control variables, the following countries are dropped from the sample: China, El Salvador, Honduras, Macedonia, Montenegro, New Zealand, Panama, Paraguay.

In contrast to the previous regression, increased mobile broadband penetration is negatively and significantly correlated with income shares of the third and fourth quintiles. This pattern would suggest that the expansion of mobile broadband could increase inequality. To put this into context, in a country that achieves full mobile broadband penetration, the third quintile would lose 0.7% of the total income share, which represents approximately 4% of the quintile's average income share.

Similar to the results in *Section 6.2*, the introduction of mobile broadband is associated with an equalizing effect with the lowest three income quintiles benefiting while the top quintile suffers. This is economically significant as well considering that for the lowest quintile a 0.23 increase would represent a 3.5% rise in their income share. The fact that the bottom two quintiles enjoy the largest benefits suggests that the introduction of mobile broadband is creating low-skill jobs accessible to the poorer segments of society. Additionally, the fact that the introduction effect disappears when using the 5% threshold indicates that the majority of the effects occurs in the very early stages of introduction. These findings imply that the installation of the network has an equalizing effect, either directly by creating employment opportunities due to the construction process or indirectly through an economic multiplier effect (i.e. the increased economic activity increases the number of workers able to eat out, buy clothes, etc. In turn, this creates service jobs for low-skill workers.). However, I am ultimately unable to identify how the introduction of mobile broadband increases the lower quintiles' income shares. Consequently, this issue presents itself as an area for future research.

Table 5 - Regressions Concerning Mobile Broadband's Effect on Income Share

	Quintile Share of Total Income				
Variables	First	Second	Third	Fourth	Fifth
Mobile Broadband Connections	-0.001	-0.004	-0.007*	-0.008*	0.019
	(0.004)	(0.004)	(0.004)	(0.004)	(0.014)
Introduction	0.249***	0.184**	0.130*	0.082	-0.647***
	(0.089)	(0.078)	(0.066)	(0.071)	(0.242)
Employment in Agriculture	-0.013	-0.018	-0.021	-0.011	0.063
	(0.014)	(0.019)	(0.020)	(0.020)	(0.067)
FDI Net Inflows	-0.000	-0.000	0.000	0.001	-0.000
	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)
Trade	-0.007***	-0.006**	-0.004	-0.001	0.019**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.009)
Inflation	0.006**	0.006*	0.005	-0.000	-0.017
	(0.003)	(0.003)	(0.004)	(0.003)	(0.012)
GDP Per Capita	0.000	-0.000	-0.000	-0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Domestic Credit Provided by Fin. Sector	-0.001	-0.003**	-0.004***	-0.004***	0.011**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)
Mean Years of Schooling	-0.108	-0.068	-0.009	0.027	0.158
	(0.085)	(0.092)	(0.102)	(0.096)	(0.333)
Natural Resource Rents	0.004	0.003	0.007	0.016	-0.031
	(0.014)	(0.017)	(0.020)	(0.021)	(0.060)
Democracy	0.141	0.137	0.061	-0.164	-0.173
	(0.174)	(0.155)	(0.185)	(0.235)	(0.546)
Government Expenditures	0.009	0.010	0.015	0.026	-0.061
	(0.028)	(0.032)	(0.032)	(0.025)	(0.110)
Non-ICT Capital	-25.717***	-11.436	3.676	19.578***	14.405
	(9.346)	(9.694)	(9.041)	(6.885)	(31.102)
Population	-0.000**	-0.000*	-0.000	-0.000	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Unemployment Rate	-0.056***	-0.042***	-0.024	-0.010	0.131**
	(0.014)	(0.016)	(0.016)	(0.015)	(0.054)
Constant	11.960***	15.953***	18.563***	22.237***	31.317***
	(1.302)	(1.121)	(1.216)	(1.307)	(4.011)
Observations	757	757	757	757	757
R-squared	0.389	0.349	0.322	0.231	0.338
Number of Countries	61	61	61	61	61
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: Errors are clustered at the country level.

Higher levels of trade are associated with a lower income share for bottom two quartiles. Conversely, for the top quartile there is a positive, significant association between trade and income share. This suggests that trade may exacerbate income inequalities within countries. This could be explained by a combination of Dinopoulos et al.'s (1999) and Egger et al,'s (2009) theories mentioned in *Section 4.3.2.5*.

Inflation has a positive and significant effect on the income share of first and second quintiles. These results should be interpreted with caution considering, as previously stated, different levels of inflation are likely to have different effects for each quintile. One possible explanation would be that higher levels of healthy inflation are associated with economic growth which in turn could increase the demand for labor and increase wages for lower quintiles.

Financial development, measured as the amount of domestic capital provided by the financial sector, favors the wealthy with a positive significant relationship for the top quintile. Conversely, it demonstrates a negative, significant relationship for second, third, and fourth quintiles. This is likely the result of the top quintile controlling a large portion of the capital and benefitting from the returns generated by lending activities.

The coefficient for the amount of non-ICT capital is negatively and significant for the first quintile and is positive and significant for the fourth quintile. This could be explained by the fact that capital abundant societies have capital-intensive industries which require high-skill workers. As a result, the high-skill wage will be proportionally higher in comparison to the low-skill wage, helping wealthier quintiles and decreasing lower quintiles' income shares.

Increasing population size is associated with increased inequality, demonstrating a negative, significant effect on the lowest two quintiles and a positive, significant effect for the top quintile. Lower quintiles may suffer in countries with large populations as GDP growth is unable to keep pace with population growth.

Unemployment has a significant, negative effect on the lowest three quintiles and a significant, positive effect for the top quintile. It is likely the unemployment does not actually benefit the top quintile but rather, due to the lost wages for the bottom quintiles, increases their comparative share.

None of the other variables demonstrate a statistically significant effect.

6.4 Absolute Income of Quintiles

Table 6 displays the results concerning how the absolute income of each quintile is affected by the introduction and expansion of mobile broadband services. Due to a lack of data, the same countries listed in *Section 6.3* are dropped from the sample. Additionally, as mentioned in *Section 4.1*, the values for each quintile's income are calculated using income shares and GDP per capita which likely introduces noise. With this limitation in mind, the expansion of mobile broadband does not appear to have a significant effect on the absolute income of any quintile. However, the introduction of mobile broadband has a significant and positive effect for the lowest quintile, increasing income by $180.09. The fact the lowest quintile experiences an increase in income due to the introduction of mobile broadband supports the theory that low-skill jobs are created either directly from the installation of the network or from the resulting economic multiplier. The discrepancies between the results illustrated in *Table 6* and *Table 5* are likely due to the aforementioned noise caused by back calculating the absolute incomes. Importantly, my results provide no evidence that mobile broadband is decreasing any single quintile's absolute income. This implies that changes in inequality are due to unequal gains rather than to income losses.

Table 6 - Regressions Concerning Mobile Broadband's Effect on Income by Quintile

	Income (USD 2010)				
Variables	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Mobile Broadband	-1.662	-1.164	-1.774	-2.377	6.497
Connections	(4.680)	(4.197)	(4.528)	(4.258)	(15.387)
Introduction	183.740*	67.526	-18.424	-69.373	-175.061
	(106.617)	(98.257)	(77.391)	(87.544)	(281.540)
Employment in Agriculture	-21.602*	-20.138	-18.651	-5.379	64.976
	(11.686)	(12.989)	(14.357)	(13.021)	(45.107)
FDI Net Inflows	-2.890	-3.403	-1.875	1.002	7.198
	(1.945)	(3.381)	(2.324)	(0.736)	(7.804)
Trade	-5.856	-5.973	-3.580	0.641	14.667
	(5.935)	(6.360)	(4.791)	(4.723)	(15.905)
Inflation	5.205*	5.652*	5.341	2.484	-18.866*
	(2.701)	(3.273)	(3.465)	(3.020)	(10.871)
GDP Per Capita	0.404***	0.608***	0.761***	0.973***	2.254***
	(0.036)	(0.033)	(0.039)	(0.038)	(0.124)
Domestic Credit Provided	-3.048	-5.095**	-6.255**	-3.655*	17.875**
by the Financial Sector	(1.853)	(2.175)	(2.406)	(2.113)	(7.922)
Mean Years of Schooling	70.376	46.333	58.807	-30.230	-141.314
	(114.650)	(97.468)	(126.819)	(143.139)	(415.333)
Natural Resource Rents	-12.434	-15.523	-20.712	-14.532	62.606
	(9.320)	(11.994)	(13.910)	(12.180)	(42.547)
Democracy	74.536	174.461	214.908	112.867	-574.708
	(69.699)	(108.988)	(148.306)	(119.231)	(418.294)
Government Expenditures	1.210	-6.273	-8.520	-5.915	20.541
	(20.007)	(25.667)	(29.531)	(33.985)	(98.988)
Non-ICT Capital	-10,113.307	7,193.833	27,095.815	40,096.019**	-63,256.823
	(9,524.940)	(12,625.666)	(17,410.007)	(18,593.819)	(53,217.857)
Population	-0.000**	-0.000***	-0.000***	-0.000**	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment Rate	-29.258*	-13.928	-12.036	-31.606**	87.021*
	(15.656)	(17.823)	(14.390)	(14.268)	(46.550)
Constant	1,959.361	2,126.480	1,335.213	1,369.270	-6,788.550
	(1,759.470)	(1,610.562)	(1,832.131)	(1,858.458)	(6,204.485)
Observations	757	757	757	757	757
R-squared	0.698	0.833	0.890	0.924	0.823
Number of Countries	61	61	61	61	61
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: Errors are clustered at the country level.

7. Robustness Checks

7.1 Heterogenous Effects

7.1.1 OECD versus Non-OECD

To examine the robustness of my previous findings, I separate the sample into OECD and non-OECD countries to determine the introduction and expansion of mobile broadband has heterogenous effects on the two groups. The results are illustrated below in *Table 7*. The regression in the first column uses the full sample, the second column includes only OECD-member countries, and the final column non-OECD countries. Given its relatively small size, splitting the original sample decreases the power of the regression to identify changes. Most of the results mirror the original regression, however, the introduction of mobile broadband loses significance in the non-OECD regression.

Table 7 – Regressions for OECD and Non-OECD Countries Respectively

Variables	Full Sample	OECD	Non-OECD
Mobile Broadband Connections	0.000	0.000	-0.001
	(0.000)	(0.000)	(0.001)
Introduction	-0.024***	-0.029*	-0.010
	(0.009)	(0.015)	(0.012)
Employment in Agriculture	0.003*	0.011***	0.000
	(0.002)	(0.003)	(0.002)
FDI Net Inflows	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)
Trade	0.001*	0.000	0.000
	(0.000)	(0.000)	(0.001)
Inflation	-0.001*	-0.002**	-0.000
	(0.000)	(0.001)	(0.000)
GDP Per Capita	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)
Domestic Credit Provided by the Financial Sector	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Mean Years of Schooling	0.010	0.003	0.018
	(0.011)	(0.009)	(0.021)
Natural Resource Rents	-0.000	0.002	-0.002
	(0.002)	(0.002)	(0.002)
Democracy	-0.017	-0.103***	-0.014
	(0.021)	(0.022)	(0.024)
Government Expenditure	0.000	0.000	0.001
	(0.003)	(0.005)	(0.003)
Non-ICT Capital	1.143	-1.023	3.122
	(1.031)	(1.135)	(1.942)
Population	0.000*	0.000	0.000
	(0.000)	(0.000)	(0.000)
Unemployment Rate	0.005***	0.002	0.007*
	(0.002)	(0.002)	(0.004)

Constant	3.081***	3.447***	3.150***
	(0.151)	(0.234)	(0.246)
Observations	793	384	409
R-squared	0.314	0.243	0.409
Number of Countries	64	32	32
Country Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: Errors are clustered at the country level.

7.1.2 Income vs. Consumption

As mentioned in *Section 4.3.1.1*, the Gini coefficient can be calculated using either income or consumption data. While this paper does not attempt to directly compare Gini coefficients between countries, it is possible that the sensitivity of Gini coefficients is dependent on whether they are income or consumption based. *Table 8* contains the original regression using the full sample in the first column, results using only income-based Gini coefficients in the second, and consumption-based Gini coefficients in the third.

Interestingly, mobile broadband penetration becomes significant and positive correlated with the income-based Gini regression, suggesting that the expansion of mobile broadband could increase inequality. The introduction of mobile broadband remains significantly and negatively correlated with the Gini coefficient. Moreover, the share of the population employed in the agricultural sector and the amount of domestic credit provided by the financial sector are significantly and positively correlated with the Gini coefficient whereas inflation, government expenditure, and gross capital formation have the opposite effect.

Conversely, there are only two statistically significant variable – government consumption and domestic credit provided by the financial sector – for the consumption-based Gini regression. This phenomenon has a few possible explanations: firstly, it is possible consumption-based Gini coefficients are less sensitive than those calculated using income data. Not only will people attempt to smooth their consumption, it also may be inelastic. For example, is it possible that the majority of the poor’s consumption is on essentials, making it less responsive to income shocks. Similarly, the richest segment of society may consume at a constant level regardless of small fluctuations in their budget. A second explanation could be that, with only 16 countries, the regression using consumption-based Gini coefficients lacks the necessary econometric power to identify correlations. Another important consideration is that, given that income-based Gini coefficients are more common in Latin America and the West compared to consumption-based calculations, these results could suffer from selection bias.

Table 8 – Regressions for Income and Consumption Calculated Gini Coefficients

Variables	Full Sample	Income	Consumption
Mobile Broadband Connections	0.000	0.001***	-0.001
	(0.000)	(0.000)	(0.001)
Introduction	-0.024***	-0.020**	-0.002
	(0.009)	(0.009)	(0.017)
Employment in Agriculture	0.003*	0.009***	0.001
	(0.002)	(0.002)	(0.002)
FDI Net Inflows	0.000	-0.000	0.001
	(0.000)	(0.000)	(0.003)
Trade	0.001*	0.000	0.001
	(0.000)	(0.000)	(0.001)
Inflation	-0.001*	-0.001	-0.000
	(0.000)	(0.000)	(0.001)
GDP Per Capita	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Domestic Credit Provided by the Financial Sector	0.000	0.000***	-0.001*
	(0.000)	(0.000)	(0.001)
Mean Years of Schooling	0.010	0.004	0.031
	(0.011)	(0.008)	(0.029)
Natural Resource Rents	-0.000	0.001	-0.002
	(0.002)	(0.002)	(0.004)
Democracy	-0.017	0.012	-0.030
	(0.021)	(0.010)	(0.032)
Government Expenditure	0.000	-0.009**	0.009***
	(0.003)	(0.004)	(0.002)
Non-ICT Capital	1.143	-0.140	3.197
	(1.031)	(1.066)	(2.255)
Population	0.000*	0.000	0.000
	(0.000)	(0.000)	(0.000)
Unemployment Rate	0.005***	0.005***	0.001
	(0.002)	(0.001)	(0.006)
Constant	3.081***	3.447***	2.660***
	(0.151)	(0.170)	(0.289)
Observations	793	566	227
R-squared	0.314	0.422	0.429
Number of Countries	64	47	17
Country Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Note: Errors are clustered at the country level.

7.2 Pre-Introduction Dummy

As stated in *Section 6.2*, I find that the introduction of mobile broadband has an equalizing effect. The fact that this effect is only significant when using the 1% threshold rather than the 5% threshold suggests that the majority of the equalizing effect occurs in the preliminary stages of the introduction of mobile broadband. However, it is possible that this effect has occurred prior to the introduction of mobile broadband and is being incorrectly attributed to the expansion of ICT services. For example, this could occur if a company opened a large factory in a country thereby creating a large amount of low-skill jobs. Then, as the purchasing power of the lower quintiles increases, a mobile phone provider expands its network in an attempt to capitalize on the new market opportunity. As such, to ensure that this effect is from the introduction of mobile broadband rather than a preceding factor, I create a dummy variable for the year prior to introduction. As demonstrated below, the dummy variable is insignificant and does not affect the significance of either the expansion or introduction variables. This supports my findings that the observed effect results from the introduction of mobile broadband and not a preceding, confounding factor.

Table 9 – Robustness Check for Introduction Effect

Variables	Log Gini
Mobile Broadband Connections	0.000
	(0.000)
Introduction	-0.036***
	(0.013)
Pre-Introduction Dummy	-0.018
	(0.011)
Employment in Agriculture	0.003*
	(0.002)
FDI Net Inflows	0.000
	(0.000)
Trade	0.001*
	(0.000)
Inflation	-0.001*
	(0.000)
GDP Per Capita	0.000
	(0.000)
Dom. Credit Provided by Fin. Sector (% of GDP)	0.000
	(0.000)
Mean Years of Schooling	0.011
	(0.010)
Natural Resource Rents	-0.000
	(0.002)
Democracy	-0.016
	(0.020)

Government Expenditure	0.000
	(0.003)
Non-ICT Capital	1.169
	(1.032)
Population	0.000*
	(0.000)
Unemployment Rate	0.005***
	(0.002)
Constant	3.069***
	(0.151)
Observations	793
R-squared	64
Number of Countries	0.318
Country Fixed Effects	Yes
Year Fixed Effects	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: Errors are clustered at the country level.

7.3 Instrumental Variable Approach

7.3.1 Simultaneity Concerns

Up until this point, this paper has not definitively identified a causal effect between the expansion of mobile broadband and changes in inequality given that the potential issues posed by the possibility of simultaneity. A country's level of inequality may partially determine when and how quickly mobile broadband is introduced and expanded. For example, societies with higher levels of inequality may experience slower expansion of mobile broadband services given that the elite may have captured the political and social systems and are focused on securing their privilege and less concerned with ensuring equal access and opportunity for the entire population (Acemoglu et al., 2008). Moreover, high inequality could foster concerns surrounding a country's long-term political stability which, when considered in concert with the large, fixed, upfront cost required to establish mobile broadband infrastructure, may deter investment and, in turn, the expansion of mobile broadband services. As a result, countries with lower inequality would experience a quicker diffusion of mobile broadband which will result in an underestimation of mobile broadband's effect on the Gini coefficient.

7.3.2 Linear IV Model

To address these concerns, I employ an instrumental variable approach in which I utilize the number of fixed-telephone subscriptions per capita twenty years prior (1982 to 1997) as an instrument for the expansion of mobile broadband. While using a non-linear first-stage model has been common in the previous literature (Czernich et al., 2011; Edquist et al., 2018), I use a linear model to sidestep the econometric issues associated with using a non-linear first stage. However, given its prevalence in past research, I include the results for the non-linear approach in Appendix B.

For this approach to be valid, the instrument must be relevant and the exclusion restriction must hold. The relevance of my instrument is rooted in the complementary role that mobile phones had vis-à-vis fixed phones in the early stages of development (OECD, 2012). While this eventually evolved towards a more competitive relationship, the initial synergies imply the existence of a correlation between the early adoption and expansion of mobile-phone technology with previous usage of fixed-phone technology. This, considered in concert with the fact that many 3G and 4G networks were constructed along previous mobile-phone infrastructure, suggests that the number of fixed-telephone subscriptions per capita 20 years prior will be related to the expansion of mobile broadband networks.

The exclusion restriction requires that the number of fixed-telephone subscriptions per capita twenty years prior have no direct effect on changes in income inequality twenty years later and to not be affected by an exogenous factor that also influences income inequality. With regards to a direct effect, it is unlikely that a change in the number of fixed-phone subscriptions between 1982 and 1983 determines shifts in quintile income shares between 2002 to 2003 given the 20 year lag and the numerous other factors affecting national economies throughout this period. As such, it is implausible that shifts in the number of fixed-phone subscriptions in the late 20th century are directly affecting changes in the Gini coefficient 20 years later. Moreover, given that fixed-phone techology was invented in the late 19th century and spread throughout the early and mid 20th century, the economic impact of fixed-phone technology will likely have occurred already, suggesting that the effect of the number of subscriptions on income inequality in the early 21st century will be minimal. This argument is supported by both the fact that, for the countries in my sample, 96% of the population was already covered by a basic mobile network in 2002 and that many countries in the dataset exhibit a decline in the number fixed telephone subscriptions in the early 21st century as traditional phone technology is replaced by mobile devices. This, considered with Edquist et al's (2018) findings that the economic effect of ICT fades over time, suggests that the economic effect of fixed-phone subscriptions on the level of inequality twenty years later will likely be neglible. As such, it is unlikely that the number of fixed-telephone subscriptions per capita twenty years prior will directly affect changes in countries' future Gini coefficients.

Furthermore, I argue that it is unlikely that an unobservable factors are biasing the relationship. Firstly, an unobservable variable that influences changes in the Gini coefficient in the first two decades of the 21st century would have occurred after the subscription levels were set, rendering it impossible for them to affect the number of fixed-phone subscriptions twenty years prior. This leaves unobservables that affect the number of fixed-telephone subscriptions in the late 20th century and also impact subsequent changes in the Gini coefficient. However, to bias the results, the unobservable factor would have to be outside the bounds of my control variables, country-fixed effects, and time-fixed effects. By including controls for the level of economic development, education, financial development and integration, democratic governance, inflation, capital stock, unemployment, openness to trade, natural resource dependence, workforce characteristics, and population size, I severely limit the channels through which an observed factor could bias the relationship. Moreover, given that include both country and time-fixed effects, the biasing, unobservable factor would also have to be a country specific issue that evolves over time. As a result, country specific policies and attitudes towards technology should also be accounted for, supporting the plausibility of the instrument.

Table 10– First-Stage Results

VARIABLES	Mobile Broadband
Fixed Telephone Subscriptions	1.129***
	(0.346)
Employment in Agriculture	0.420
	(0.459)
FDI Net Inflows	-0.002
	(0.007)
Trade	-0.002
	(0.052)
Inflation	0.062
	(0.050)

GDP Per Capita	0.000
	(0.000)
Domestic Credit Provided by the Financial Sector	0.063
	(0.055)
Mean Years of Schooling	0.571
	(2.124)
Natural Resource Rents	0.032
	(0.250)
Democracy	-5.058
	(5.556)
Government Expenditure	0.650
	(0.413)
Non-ICT Capital	542.610***
	(185.864)
Population	0.000
	(0.000)
Unemployment Rate	0.119
	(0.251)
Observations	781
Number of Countries	64

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: Errors are clustered at the country level.

With one endogenous regressor and one instrument, my model is exactly identified and, with an F-statistic of 10.63, my instrument is not weak. The first stage I shown above and the second stage below.

Table 11 – Second-Stage Results

Variables	Dependent Variable: Log Gini
Mobile Broadband Connections	0.003*
	(0.002)
Employment in Agriculture	0.001
	(0.002)
FDI Net Inflows	0.000
	(0.000)
Trade	0.001*
	(0.000)
Inflation	-0.001**
	(0.000)
GDP Per Capita	0.000
	(0.000)

Domestic Credit Provided by the Financial Sector	-0.000
	(0.000)
Natural Resource Rents	0.003
	(0.010)
Mean Years of Schooling	-0.000
	(0.002)
Democracy	0.014
	(0.020)
Government Expenditure	-0.002
	(0.003)
Non-ICT Capital	-0.559
	(1.619)
Population	0.000
	(0.000)
Unemployment Rate	0.004***
	(0.002)
Observations	781
R-squared	0.205
Number of Countries	64
Country Fixed Effects	Yes
Year Fixed Effects	Yes
F-Statistic	10.63

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: Errors are clustered at the country level.

The second-stage results suggest that the expansion of mobile broadband has a positive and significant effect on income inequality. Similar results are found using the non-linear estimation although they are smaller in magnitude – 0.002 versus 0.003. These findings are supported by the results from *Section 6.3* where the expansion of mobile broadband decreased the income shares of the third and fourth quintiles.

8. Discussion

In this section I consider the limitations of this paper, identify future research opportunities, and discuss the potential policy implications of the findings. First, the nature of the data set limits the results. The panel is unbalanced due to the fact statistics on inequality are not compiled on an annual basis in the majority of countries. As a result, there are fewer observations which decreases the power of the study to identify relationships between mobile broadband and inequality. Moreover, despite its prevalence in the literature, the Gini coefficient is an imperfect measure. Firstly, the Gini coefficient can be measured in terms of income or consumption. As explained by the International Monetary Fund's World Economic Outlook (IMF Research Department, 2007), Gini coefficients calculated using consumption data tend to be lower in absolute terms that those calculated using income data and are more often used by developing countries where self-employment and home agriculture account for a larger percentage of consumption. Secondly, there is not a standardized method of collecting data regarding consumption and income; differences in definitions of consumption or income, how surveys are conducted, and who is surveyed could decrease the cross-country consistency of the measurements. Lastly, due to a lack of data, many Asian countries are excluded and no countries from Africa or the Middle East are represented in the regression. Consequently, the findings may lose relevance outside of Europe, North America, South America, and possibly Asia. For example, it is conceivable that the effect mobile broadband has on inequality may be very different in a country such as Uganda, where a large portion of the population still does not have access to electricity, than in a more developed country such as the United States or Canada.

Moreover, the nature of the study limits the results; finding a natural experiment for a large, cross-country study is extremely difficult and, consequently I have to use an instrumental variable approach to address the possibility of endogeneity. While I argued for the plausibility of the assumptions I made with regards to my instrument, the exclusion restriction is ultimately untestable. As such, it is important to interpret the results with a caution.

Despite these limitations, this paper does have some initial policy implications. The findings suggest that the introduction of mobile broadband has an equalizing effect. Considering these results in concert with previous findings identifying mobile broadband's positive impact on economic growth (Edquist et al. 2018; Röller et al., 2001; Waverman et al., 2005) provides optimism that investments in future networks could be used as a viable option for promoting sustainable and equitable economic growth. Given that this paper lacks the specificity necessary to identify exactly why this phenomenon occurs, further research is necessary to ensure societies are able to realize the full benefits from the introduction of mobile broadband.

Conversely, the results concerning the income shares of quintiles suggest that the expansion of mobile broadband may ultimately result in higher levels of inequality. The regression identifies a negative and significant effect of mobile broadband on the third and fourth quintiles' income shares. These findings are supported by the linear IV specification which finds that the expansion of mobile broadband increases inequality. These findings suggest it may be important to explore policy options to ensure that the long-term benefits of mobile broadband are distributed equitably. Such policies could include training programs for workers and business owners on how to best incorporate ICT technology into their business and ensuring rural, poor, and hard to reach populations are connected as well. Unfortunately, similar to the equalizing effect due to the introduction of mobile broadband, this study lacks the data necessary to explain exactly why these income shifts occur. Understanding the specifics of these transfers is integral to crafting appropriate policies and ensuring equitable growth. As such, understanding the channels through which mobile broadband affects quintile income share presents itself another opportunity for future research.

9. Conclusions

In this paper I use a fixed-effects model with unbalanced panel data to estimate the effect that the introduction and expansion of mobile broadband has on economic inequality. I find that the introduction of mobile broadband is associated with a 2.4% decrease in the Gini coefficient. This result it corroborated by regressions concerning quintile income share where the introduction of mobile broadband is associated with an increase in the income shares of the bottom three quintiles. Conversely, there is evidence suggesting that the expansion of mobile broadband increases inequality with the income shares of the third and fourth quintiles falling with the expansion of mobile broadband. However, I do not find that any quintile's absolute income suffers due to the introduction and expansion of mobile broadband indicating that the increased inequality is likely due to heterogenous gains.

Overall, these results provide empirical support for the using investment in mobile networks as a tool to promote inclusive economic growth. My findings join a growing body of literature identifying both the economic and social benefits of ICT (Czernich et al., 2011; Edquist et al., 2018; Jack et al., 2014; Jensen et al., 2007). While ensuring the provision of basic needs such as access to clean water, food, and shelter rightly trumps financing ICT infrastructure projects, as countries advance and begin contemplating projects to help grow the economy and decrease poverty, investing in ICT networks should be considered.

10. References

Acemoglu, D. (2000). Technical Change, Inequality, and the Labor Market. NBER Working Paper Series, Working Paper 6565.

Acemoglu, D., & Robinson, J. (2008). Persistence of Power, Elites, and Institutions. *The American Economic Review, 98*(1), 267-293.

Akerman, A., Gaarder, I., Mogstad, M. (2015). The Skill Complementarity of Broadband Internet. *Quarterly Journal of Economics, 130(4),* 1781-1824.

Alesina, A., & Rodrik, D. (1994). Distributive politics and economic growth. *Quarterly Journal of Economics*, 109(2), 465-490.

Anand, S., & Kanbur, S. (1993). The Kuznets process and the inequality – development relationship. *Journal of Development Economics, 40*(1), 25-52.

Angrist, J., & Pischke, J., (2008). Mostly Harmless Econometrics: An Empiricist's Companion. Princeton University.

Atasoy, H. (2013). The Effects of Broadband Internet Expansion on Labor Market Outcomes. Industrial and Labor Relations Review, 66(2), 315-345.

Australian Bureau of Statistics, Household Economic Wellbeing Indicators (2018). *Income Gini Coefficient and Income Shares.*

Autor, David H. (2014), Skills, Education and the Rise of Earnings Inequality Among the ´Other 99 Percent, *Science*, vol. 344, pp. 843–851.

Ball, C., & Creedy, J. (2016). Inequality in New Zealand 1983/84 to 2012/13. *New Zealand Economic Papers*, *50*(3), 323-342.

Berman, E., Bound, J., Griliches, Z., (1994). Changes in the Demand for Skilled Labor within U.S. Manufacturing: Evidence from the Annual Survey of Manufacturers. *The Quarterly Journal of Economics, 109(2),* 367-397.

Berman, E., Bound, J., Machin, S. (1997). Implications of Skill-Biased Technological Change: International Evidence. NBER Working Paper Series, Working Paper 6565.

Bulíř, A. (2001). Income Inequality: Does Inflation Matter? *IMF Staff Papers, 48*(1), 139-159.

Campante, F. and Do, Q. (2007). Inequality, Redistribution, and Population. KSG Working Paper No. RWP07-046.

Center for Systemic Peace. 2018. Polity IV Annual Time-Series, 800-2017.

Czernich, N., Falck, O., Kretschmer, T., & Woessmann, L. (2011). Broadband Infrastructure and Economic Growth. *The Economic Journal, 121*(552), 505-532.

Deininger, K., & Squire, L. (1998). New ways of looking at old issues: inequality and growth. *Journal of Development Economics, 57*, 259-287.

Dinopoulos, E., & Segerstrom, P. (1999). A Schumpeterian Model of Protection and Relative Wages. *The American Economic Review, 89*(3), 450-472.

Edquist, H., Goodridge, P., Haskel, J., Li, X., Lindquist, E. (2018). How Important are Mobile Broadband Networks for Global Economic Development? *35th IARIW General Conference.*

Egger, H., & Kreickemeier, U. (2009). Firm Heterogeneity and the Labor Market Effects of Trade Liberalization. *International Economic Review, 50*(1), 187-216.

Ericsson. (2019). *Ericsson Mobility Report.*

Gafar, J. (2005). Do the Poor Benefit from Public Spending? A Look at the Evidence. *The Pakistan Development Review, 44*(1), 81-104.

Galor, O., & Zeira, J. (1993). Income Distribution and Macroeconomics. *The Review of Economic Studies, 60*(1), 35-52.

Geroski, P. (1999). Models of Technology Diffusion. London, Centre for Economic Policy Research.

Griliches, Z. (1957). Hybrid Corn: An Exploration in the Economics of Technological Change. *Econometrica, 25*(4), 501-522.

Glyn, A. (1995). The Assessment: Unemployment and Inequality. *Oxford Review of Economic Policy, 11*(1), 1-25.

Haskel, J., Slaughter, M. (1998). Does the Sector Bias of Skill-Biased Technical Change Explain Changing Wage Inequality? NBER Working Paper Series, Working Paper 6565.

Hjort, J., & Poulsen, J. (2019). The Arrival of Fast Internet and Employment in Africa. *American Economic Review, 190(3),* 1032-1079.

International Monetary Fund. (2007) World Economic Outlook October 2007 – Globalization and Inequality. *World Economic and Financial Surveys.*

Jack, W., & Tavneet S. (2014). Risk sharing and transactions costs: Evidence from Kenya's mobile money revolution. *American Economic Review* 104*(1),* 183-223.

Jaumotte, F., Lall, S., & Papageorgiou, C. (2013). Rising Income Inequality: Technology, or Trade and Financial Globalization? *IMF Economic Review, 61*(2), 271-309. Retrieved from http://www.jstor.org/stable/43302166

Jensen, R. (2007). The Digital Provide: Information (Technology), Market Performance, and Welfare in the South Indian Fisheries Sector. *The Quarterly Journal of Economics, 122*(3), 879-924.

Jorgenson, D., Mun H., & Stiroh, K. (2008), A Retrospective Look at the U.S. Productivity Resurgence, *Journal of Economic Perspectives*, vol. 22, pp. 3–24.

Korean Statistical Information Service. (2018). Statistical Database.

Kuznets, S. (1955). Economic Growth and Income Inequality. *The American Economic Review, 45*(1), 1-28.

Larrain, M. (2015). Capital Account Opening and Wage Inequality. *The Review of Financial Studies, 28*(6), 1555-1587.

Marchand, J. (2015). The distributional impacts of an energy boom in Western Canada. *The Canadian Journal of Economics / Revue Canadienne D'Economique, 48*(2), 714-735.

Matins-Bekat, M., & Kulkarni, K. (2009). Income Distribution and Economic Growth: The Case of Brazil. *The Journal of Developing Areas, 43*(1), 341-351.

Mugisha, F., Odusola, A., Workie, Y., & Reeves, W. (2017). Income Inequality and Population Growth in Africa.

National Bureau of Statistics of China. (2018). Statistical Yearbook.

OECD. (2012). Fixed and Mobile Networks: Substitution, Complementarity and Convergence, *OECD Digital Economy Papers, No. 206, OECD Publishing, Paris.*

Oliner, S., & Sichel, D. (2000). The Resurgence of Growth in the Late 1990s: Is Information Technology the Story? *The Journal of Economic Perspectives, 14*(4), 3-22.

Paukert, F. (1973). Income distribution at different levels of development: A survey of evidence. *Int'l Lab. Rev., 108*, 97.

Ravallion, M. (2001). Growth, Inequality and Poverty: Looking Beyond Averages. *World Development, 29*(1), 1803-1815.

Röller, L., & Waverman, L. (2001). Telecommunications Infrastructure and Economic Development: A Simultaneous Approach. *The American Economic Review, 91*(4), 909-923.

Roser, M. and Ortiz-Ospina, E. (2017). Global Extreme Poverty. *Published online at OurWorldInData.org.*

Solow, R. (1987). We'd better watch out, *New York Times Book Review, 36.*

Solt, F. (2011). Diversionary Nationalism: Economic Inequality and the Formation of National Pride. *The Journal of Politics, 73*(3), 821-830.

State Statistical Office of Macedonia. (2017). MakStat database.

Stolper, W., & Samuelson, P. (1941). Protection and Real Wages. *The Review of Economic Studies*, *9*(1), 58-73.

Ulfelder, J. (2012). Democracy/Autocracy Dataset.

United Nations Development Programme. (2017). *Human Development Data (1990-2017).*

United Nations Development Programme. (2017) Human Development Reports – Mean Years of Schooling.

UNU-WIDER, (2018). World Income Inequality Database (WIID4).

The World Bank, Data Bank (2017). *GDP Per Capita.*

Wahid, A., Shahbaz, M., Shah, M., & Salahuddin, M. (2012). Does Financial Sector Development Increase Income Inequality? Some Econometric Evidence from Bangladesh. *Indian Economic Review, 47*(1), new series, 89-107.

Waverman, L., Meloria M., & Melvyn F. (2005). The Impact of Telecoms on Economic Growth in Developing Countries. In Africa: The Impact of Mobile Phones. Vodafone Policy Paper 3, 10-23.

Winegarden, C. (1979). Schooling and Income Distribution: Evidence from International Data. *Economica, 46*(181), new series, 83-87.

World Bank. (2016). *World Development Report*.

Yue, H. (2011) Income Inequality, Economic Growth and Inflation: A Study on Korea. *International Journal of Economics and Research, 2(5)*, 14-21.

Appendix A: Non-Linear IV

a. First-Stage Regression

Due to its presence in previous literature I include a non-linear IV approach similar to Czernich et al. (2011) and Edquist et al. (2018). I employ a non-linear first stage model, using the number of mobile phone subscriptions per 100 users in 2002 (ITU 2018) to predict expansion of mobile broadband within countries. I use a non-linear, logistic growth function based on the findings of a prior research (Griliches et al., 1957; Geroski et al., 1999; Czernich et al., 2011; Edquist et al., 2018) that suggests that technology diffusion follows an S-shaped diffusion curve.

To obtain the predicted expansion of mobile broadband, I use the technology diffusion equation constructed below. I begin with a linear function to model the maximum penetration of mobile broadband as it relates to the number of mobile phone subscriptions in 2002:

$$MMBP_i = \theta + \theta_1 X_{i2002} \tag{8}$$

Where $MMBP_i$ is the maximum penetration rate of mobile broadband in country i, X_{i2002} is the number of mobile phone subscriptions per 100 users in country *i* in 2002. This equation relates the the number of mobile phone subscriptions per 100 users in 2002 with the floor and ceiling of mobile broadband penetration. Having identified these values, I use the equation below to approximate the slope of the diffusion of mobile broadband:

$$MobileBroadband_{it} = \frac{MMBP_i}{1+exp[-\beta(t-\tau)]} + \varepsilon_{it} \tag{9}$$

Where $MobileBroadband_{it}$ is the level of mobile broadband penetration in country *i* in year *t* and $MMBP_i$ is defined in *Equation 8.* β and τ are constants that determine the inflection point for the diffusion of mobile broadband as well as the speed. ε_t is the error term. I then combine *Equation 8* and *Equation 9* to obtain the following non-linear equation:

$$MobileBroadband_{it} = \frac{\theta+\theta_1 MobilePhonePer100_{i2002}}{1+exp[-\beta(t-\tau)]} + \varepsilon_{it} \tag{10}$$

This equation is in line with Griliches et al.'s (1957) model of technology diffusion which suggests that the "origins, slopes, and ceilings" are the crucial parameters for predicting technology diffusion. *Table 12* illustrates the results for the first-stage, non-linear least squares model. Due to data restrictions, Macedonia and Serbia are dropped from the sample.

Table 12 **- Diffusion Equation**

	$Constant$ (θ)	$Mobile\ Subs$ (θ_1)	Speed β	Inflection τ
	49.06***	0.701***	0.380***	11.24***
	(2.010)	(0.0328)	(0.0192)	(0.232)
Observations		969		
R-squared		0.918		

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

As shown above, the number of mobile subscriptions per 100 users in 2002 is statistically significant at the 1% level as are the rest of the indicators. τ represents the inflection point which occurs in 2013 for most countries.

Using the model above, I predict the diffusion of mobile broadband for countries in my sample using the number of mobile subscriptions per 100 users in 2002. Below, *Figure 5* plots the predicted expansion of mobile broadband against the actual expansion by country. The predicted values appear to be in line with the the actual expansion of mobile broadband with the exceptions being South Korea, the United States, Thailand, and Australia. However, given that there does not appear to be a consistent bias towards under or overestimation, it is likely that this divergence is due to country specific factors (e.g. supportive policy for the expansion of broadband, political upheaval, etc.).

For this approach to be valid, the instrument must be relevant and the exclusion restriction must hold. Predicted values based on the number of mobile subscriptions per 100 users in 2002 should yield a relevant relevant given that many 3G and 4G networks were constructed along existing mobile phone infrastructure which suggests a country's uptake of mobile broadband services is likely to be highly correlated with its adoption rate of previous mobile phone technology[5].

Figure 5– Predicted Vs. Actual Expansion of Mobile Broadband

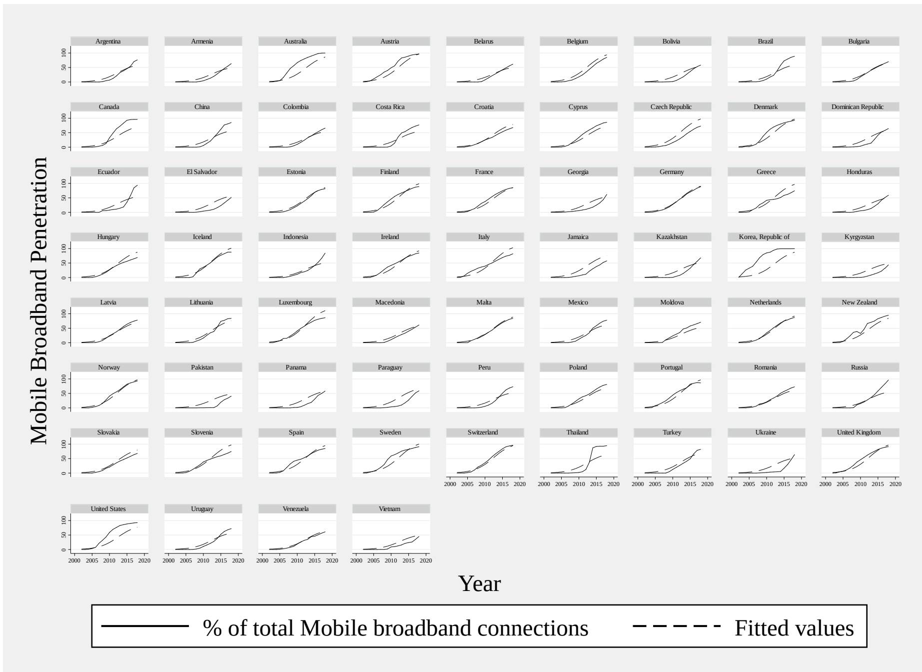

Figure 5 – The expansion of mobile broadband by country. Source: Author's rendering using data from the GSMA Wireless Intelligence Database (2018).

The exclusion restriction requires that the level of mobile phone penetration in 2002 does not have an impact on subesquent changes in the Gini coefficient. This is plausible given that, rather than using multiple years, I only use the number of mobile phone subscriptions in 2002 to predict the true diffusion process from 2002 to 2017. Moreover, in my sample a large majority of the population was already covered by a mobile network in 2002[6]. Given that the economic effects of ICT technology tend to fade over time (Edquist et al., 2018), it is likely that the economic effects generated by non-broadband capable mobile phones have occurred previously and are fading. The effect of non-broadband capable phones will be further diminished as they are replaced by broadband capable devices. As such, it is unlikely that the number of mobile phone subscriptions per 100 users in 2002 will affect changes in countries' future Gini coefficients over the following

[5] Testing for a weak instrument, I find a χ^2 of 183.69 which suggests the instrument is not weak.
[6] 96% for countries with data available for 2002 and 90% for countries with data available for at least one year between 2001-2003.

fifteen years except through the spread of mobile broadband.

Another critique of this identification strategy is that it will generate "consistent estimates only if the non-linear first-stage model is correctly specified" (Czernich et al., 2011). While it is possible that this model is correctly specified given the literature suggesting that technology follows a S-shaped diffusion path (Geroski, 1999), the model will suffer from bias if the model is not perfectly specified and, as such, the results should be interpreted with caution[7].

b. Second-Stage Results

Using the predicted values based on the number of mobile subscriptions per 100 users in 2002 computed in the first stage, the second-stage regression attempts to identify a causal relationship between the expansion of mobile broadband services and changes in the Gini coefficient. The results are shown in *Table 13.*

Table 13 – Second-Stage Results

Variables	Log Gini
Mobile Broadband Connections	0.002**
	(0.001)
Employment in Agriculture	0.002
	(0.002)
FDI Net Inflows	-0.000
	(0.000)
Trade	0.000
	(0.000)
Inflation	-0.001*
	(0.000)
GDP Per Capita	0.000
	(0.000)
Domestic Credit Provided by the Financial Sector	0.000
	(0.000)
Mean Years of Schooling	0.007
	(0.011)
Total Natural Resources Rent	-0.000
	(0.002)
Democracy	-0.002
	(0.018)
Government Expenditure	-0.001
	(0.003)
Non-ICT Capital	0.835

[7] For this reason, Professor Hausmann deemed non-linear first-stage regressions in 2SLS models the "forbidden regression". The non-linear model must be correctly specified to yield accurate results and, as such, should be interpreted with caution.

	(1.058)
Population	0.000*
	(0.000)
Unemployment Rate	0.005***
	(0.002)
Constant	3.148***
	(0.152)
Observations	782
Number of Countries	63
R-squared	0.312

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

The results suggest that the expansion of mobile broadband has a statistically significant and positive effect on a country's Gini coefficient. Given the estimated coefficient, a country in which the percent of mobile broadband capable connections grow from zero to full coverage would experience a 20% increase in its Gini coefficient.

Appendix B: Education and Inequality Graph

Figure 6 – Evolution of Inequality and Education

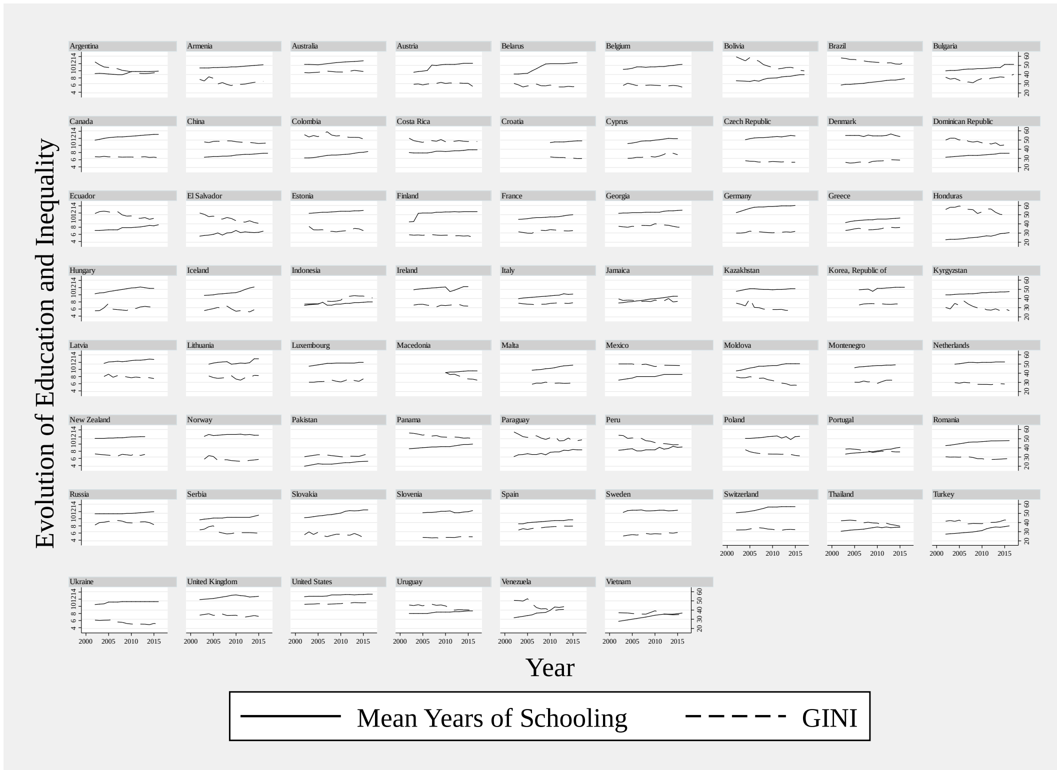

Figure 6 – Evolution of the Gini coefficient and the mean number of years of education for the population 15 years and older by country. Source: Author's rendering using data from the United Nation's World Income Inequality Database (2018) and the United Nations Development Programme's Human Development Report (2017).

Appendix C: Full Descriptive Statistics

Table 14 – Full Descriptive Statistics

Variable	Mean	Std. Dev.	Min.	Max.	Obs.
Gini Coefficient (First Obs.)	0.4	0.1	0.2	0.6	69
Gini Coefficient (Last Obs.)	0.4	0.1	0.2	0.5	69
Bottom Quintile's Income Share (First Obs.)	6.7	2.4	1.7	10	65
Bottom Quintile's Income Share (Last Obs.)	7	2	3.1	10.1	65
Top Quintile's Income Share (First Obs.)	44.6	8.1	33.8	62.4	65
Top Quintile's Income Share (Last Obs.)	42.8	6.1	34	57.6	65
First Quintile's Average Income (First Obs.)	$7,591.4	$9,413.2	$137.2	$40,390	65
First Quintile's Average Income (Last Obs.)	$8,776.8	$9706.3	$346.4	$40,456.72	65
Top Quintile's Average Income (First Obs.)	$40,402.7	$41,595.4	$1,323.5	$188,568.3	65
Top Quintile's Average Income (Last Obs.)	$48,121.6	$46,458	$1,940.7	$202,625.8	65
Mobile Broadband Penetration (% of total devices)	22.9	26	0	99.5	916
Year of MBB Introduced (1% Rate)	2007	2.1	2003	2014	69
Year of MBB Introduced (5% Rate)	2008	2.4	2003	2014	69
OECD	0.45	0.5	0	1	908
GDP Per Capita (Constant 2010 USD)	21,290.7	22,186.6	676.3	111,968.3	908
Trade	92.4	51.8	22.1	410.2	907
Net Inflow of FDI (% of GDP)	7	24.4	-58.3	451.7	908
Non-ICT Capital (Billions USD)	4,064.2	9,916.9	25.7	80,000	837
Domestic Credit Provided by the Financial Sector	92.1	64.9	5.5	316.6	876
Inflation Rate	5.1	6.9	-4.5	81.1	900
% of Population Employed in Agriculture	14.8	13.3	0.5	62	908
Total Natural Resource Rent (% of GDP)	3	4.8	0	32.4	898
Mean Years of Schooling	10.2	2.2	3.8	14.1	908

Democracy	0.8	0.4	0	1	887
Government Spending (% of GDP)	17	4.3	5.5	30	907
Population	60,400,000	182,000,000	289,400	1,380,000,000	837
Unemployment Rate	8.1	4.8	0.4	32	908

Appendix D: Gini Coefficient by Country

Figure 7 – Evolution of Gini Coefficient by Country

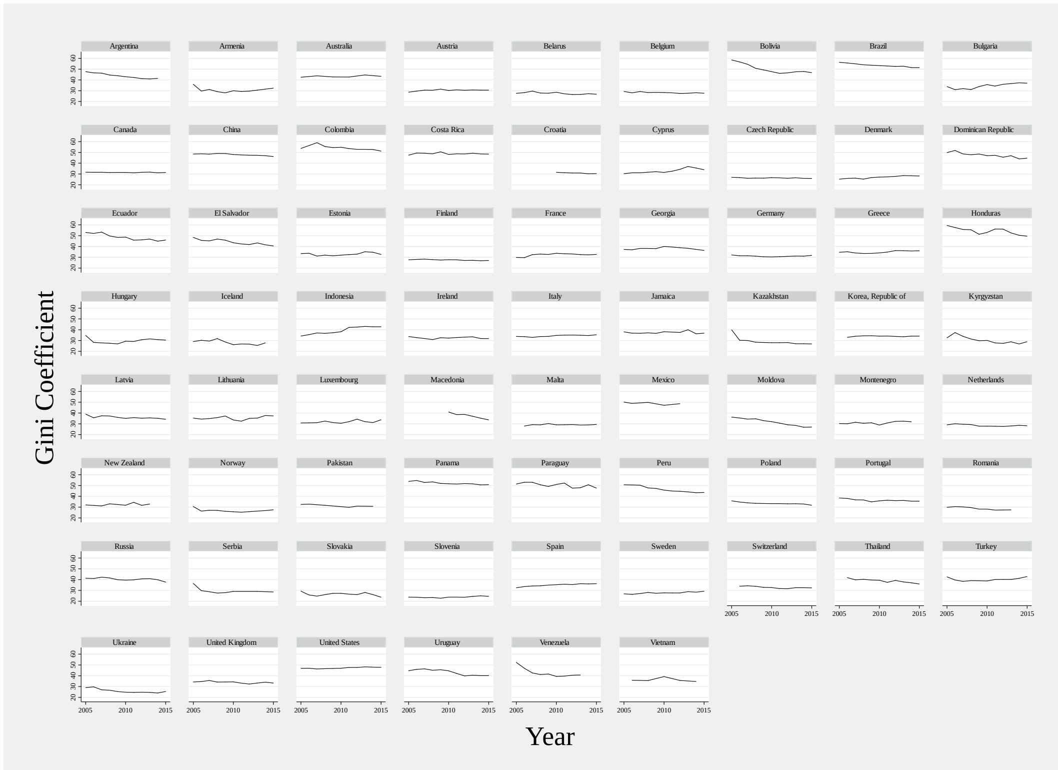

Figure 7 – Evolution of the Gini coefficient by country over time. Source: Author's rendering using data from the United Nation's World Income Inequality Database (2018).

Appendix E: Calculation of the Gini Coefficient

Figure 8 – Graph of the Gini Coefficient

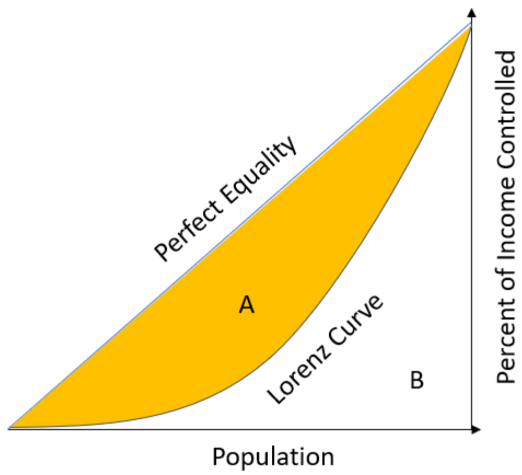

Figure 8 – Graphical representation of the Gini coefficient. Source: Author's rendering.

The Gini coefficient is expressed as a percentage between zero and one which attempts to quantify inequality within societies. The value zero represents perfect equality and one represents perfect inequality. The 45-degree line represents a perfectly equal society – e.g. 20% of the population earns 20% of the income. The Lorenz curve shows the actual distribution of wealth within a society. The Gini coefficient is then calculated using the following equation:

$$Gini = 1 - 2\int_0^1 L(x)dx \tag{11}$$

Where *L(x)* is the function representing the Lorenz Curve. *Figure 8 above* provides a graphical representation of the Gini coefficient where the value can be approximated using the formula below:

$$Gini = 2 * \frac{A}{A+B}$$