Stockholm School of Economics
Department of Economics
5350 Master's Thesis in Economics
Academic Year 2015-2016

Connecting the World:

Exploring the Economic Impact of Mobile Broadband Networks

Edward R. Lindquist (40614)

Abstract: In this thesis, we set out to investigate mobile broadband and the economic impact that these technologies have had. This is a crucial topic in light of the rapid expansion of mobile telephony and mobile broadband. The basic findings are in line with those from previous ICT-based studies. Applying two-way fixed effects and GMM estimation, mobile broadband is observed to have a positive association with economic development. This association was explored and repeatedly confirmed using a variety of econometric methods that attempted to tackle reverse causality issues, eventually suggesting a causal effect of mobile broadband. A second goal of this thesis was to investigate if the impact of mobile broadband differed based on a country's development status. However, at the current moment little can be said conclusively. Overall, while it seems that mobile broadband has a positive effect on economic development, more research with better quality data is needed to draw even deeper conclusions.

Keywords: ICT, mobile broadband, 3G networks, economic development, panel data

JEL Classification: L86, L96, C23, 050

Supervisors: Martina Björkman Nyqvist (SSE), Harald Edquist (Ericsson)
Date Submitted: January 25, 2016
Date Examined: January 13, 2016
Discussant: Marisa Basten
Examiner: Chloé Le Coq

Acknowledgements

This thesis was written in collaboration with Ericsson Research. I would like to sincerely thank the company and staff for dedicating valuable resources towards the completion of this study.

I also wish to thank both Martina Björkman Nyqvist at the Stockholm School of Economics and Harald Edquist at Ericsson Research for their invaluable input during the supervision of this thesis.

Several classmates in the M.Sc. Economics program provided insightful comments during seminars that were vital to the learning process.

Finally, I would not be where I am without my friends and family. To my friends: thank you for providing some necessary stress relief throughout the semester. To my family: thank you for continuing to support me no matter where life takes me. To all: your love and support has meant the absolute world to me, more than I can ever properly explain.

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1 Introduction

The role of technology in growth has been explored by economists for decades, and quantifying this role, and which technological tools have the greatest impact, has been the goal of many a researcher. Innovation and technological change as agents of economic growth have now become commonplace in standard economic models, and it has long been thought that this technological change is due in part to the spread of information and communications technologies (ICT).

In today's global economy, ICT have become ever-present. There are expected to be 3.2 billion Internet users around the globe by the end of 2015, two billion of which hail from developing countries; furthermore, more than 7 billion mobile cellular subscriptions will exist, and this continues to be the most dynamic market segment in terms of growth (ITU 2015). The rapid growth of ICT, especially in developing areas, has led to these tools becoming a cornerstone of day-to-day life, and an integral part of the social and business environment, so much so that some have argued for ICT's role as a general purpose technology (GPT) enabling further innovation and influencing economic growth and productivity beyond the normal effects of a regular capital good.[1] This argument is especially convincing as knowledge and information, the main byproducts of ICT, have become increasingly important to economic activity. However, as of yet ICT have still not penetrated some of the most remote parts of the globe, with many rural areas still lacking Internet, fixed telephone lines, and adequate cellular coverage.

The literature spanning ICT and its effects is now considerably large, but as one narrows down to specific forms of ICT the amount of research done shrinks considerably. Previous research has found that the impact of ICT, including core 2G networks, is important for economic development (Crandall & Singer 2010; Williams et al 2012; Cardona et al 2013). However, attention has recently turned to mobile telecommunications and mobile broadband networks, and the impacts that these technologies can have, especially as usage spreads into developing economies and penetration rates subsequently increase.

Mobile broadband networks are thus interesting to investigate for a number of reasons. Landline subscription rates are falling rapidly in most parts of the world, and fixed telephony systems are less and less likely to play a role in the expansion of ICT in the future. Growth is likely to come primarily from mobile telephony, and this is especially true in low-income communities. The total number of mobile subscriptions was about 7.2 billion in early 2015, with growth of 5 percent year on year, and the number of smartphone subscriptions is expected to surpass those for basic phones in 2016 (Ericsson 2015), due in part to greater affordability in developing markets. According to the Ericsson Mobility Report (2015), smartphone subscriptions are set to more than double by 2020.

[1] General purpose technologies are technologies that can affect an entire economy. The characteristics of these technologies are: applicability across a broad range of uses; wide scope for improvement, experimentation, and elaboration; ease process for inventing and producing further new products (Bresnahan & Trajtenberg 1995; Cardona et al 2013).

By this time, 90 percent of the global population will have a mobile phone, while 70 percent will have a smartphone. However, smartphone growth would not be possible without complementary network growth: of the world,'s 7.4 billion people, 3G coverage reached 69% of the global population in 2015, up from 45% just four years prior. However, there is still massive disparity between urban and rural areas: while urban areas (comprising 4 billion people) had 89% global coverage, rural areas had only 29% coverage (ITU 2015). The potential for development and productivity gains to spread to remote and rural areas, due to 3G technology's inherent mobile characteristics, means that research on the impact of mobile broadband networks could be particularly valuable in the area of development economics.

A wealth of data is only now becoming available, meaning that while some research does exist there is not yet substantial research available on the effects of 3G and mobile broadband. While the evolution of 2G did eventually allow Internet connectivity, 3G is arguably the first mobile broadband generation that brought connectivity to the masses and allowed ample data usage at fast speeds.[2] Even less research has been undertaken on the impacts of 4G technology given its relative newness. Yet, 5G subscriptions should already be commercially available by 2020, and uptake is expected to be even faster than for 4G. This research could help illuminate the potential effects that increasingly faster mobile broadband networks may have in the future, and the role that these networks might play in economic development. Due to renewed interest in the exact role of ICT in economic and productivity growth, the ability to provide accurate, up-to-date information about the impacts of emerging technologies is more important than ever, both for the technology industry as a whole as well as to properly direct government policy.

Overall, previous research into ICT has found significant and positive effects on economic development. However, these studies have often focused on established technologies, such as fixed telephone lines or computers, and focus has most often been on the experience of industrialized high-income nations. Little research has focused on mobile technologies because of their relative newness as a critical tool in today's society; furthermore, even less focus has been placed on the effect of these technologies in the many parts of the world that currently lack traditional ICT public infrastructure. One could posit two potential scenarios: the first is that mobile broadband has a stronger effect in low-income than in high-income countries as these new technologies act as substitutes for more traditional infrastructure like fixed lines; the second is that a higher effect is seen in high-income than in low-income countries as low-income communities may lack the capabilities and complementary network structures to fully exploit the benefits of mobile broadband technologies. Thus far research into how other ICT effects differ for developing and developing countries has been mixed.

Thus, this thesis will investigate the macroeconomic impacts of mobile broadband technologies on economic development, using econometrics methods and a cross-country panel data set. The

[2] The ability to use data, using GPRS and later EDGE, was an intermediary evolution between the 2G and 3G technologies.

research questions are as follows:

- From a macroeconomic perspective, what effect has mobile broadband had on economic development across countries?
- If an effect exists, does this effect differ based on a country's development status as measured by income levels?

We might expect that less advanced networks, like 2G, will continue to play a significant role in low- and middle-income countries while more advanced networks, such as 3G and 4G, will play a role in high-income countries. This may prove difficult though due to limitations on data, especially when disaggregating by country income status. However, we also expect that mobile broadband networks viewed simultaneously, using a proxy such as smartphone adoption, will have an effect on economic development in a full-country sample.

The paper is organized as follows. Section 2 provides a survey of the relevant literature on ICT, telecommunications, and mobile technologies, and their related economic effects. Section 3 details the methodology, including the data used, the model specification, and the empirical implementation of the model. Section 4 presents initial results and analysis, while section 5 explores robustness checks for the model and section 6 details extensions aimed at tackling potential endogeneity issues. Section 7 presents a summary of the results, discusses validity and limitations, and presents possibilities for future research. Finally, section 8 concludes the study.

2 Related Literature

In this section, an overview of previous research is given, split by the type of technology researched. There has been a considerable amount of research on the economic impact of varying information and communications technologies (ICT) on growth, and it is still difficult at times to definitively declare an academic consensus. Information and communications technologies, commonly referred to as ICT, have no universal definition since the concepts involved evolve and change, almost on a daily basis. The OECD (2009:11) states that ICT products must "primarily be intended to fulfill or enable the function of information processing and communication by electronic means, including transmission and display." Thus, the term is often used to encompass any technology that can store, retrieve, transmit or receive electronic information in a digital format; this includes audio-visual systems, telecommunications technology, and computers. However, difficulties in establishing a classification system for ICT products, due to the rapidly changing character of ICT goods and services, have been recognized by the WPIIS since 1998. Because of this, investigation into previous literature will begin first by looking at the ICT sector as a whole, before delving deeper and looking more specifically at telecommunications and mobile telephony, and finally focusing on research on the effects of fixed and wireless broadband. At the end of this section, we outline common methods and parameters used to investigate ICT, as well as the contribution that this study hopes to make to the academic sphere.

2.1 Information and Communications Technologies (ICT)

Fifty years ago economists considered technological change as the single most important parameter for growth and labor productivity (Koutroumpis 2009). Robert Solow (1957) highlighted the importance of technological progress in producing long-run GDP per capita growth: ever more efficient use of limited resources is necessary to produce sustainable economic growth over the long-term. Yet, researchers failed to see any effects of ICT in productivity estimates throughout the 1970s and 1980s, referred to as the Solow Paradox after Solow commented "You can see the computer age everywhere but in the productivity statistics" (Solow 1987:36). A slowdown in productivity growth in the US and other countries around the world lead researchers to question if the effects of ICT adoption had run their course, and subsequent research models used to measure technological effects on growth varied significantly.

Current research into ICT can be classified in a number of ways (Edquist 2014, Cardona et al 2013): based on methodology used (non-parametric growth accounting exercises vs. parametric econometric estimations); aggregation level (country, industry, or firm level); or ICT product/measure (IT hardware/software, data communication, telecommunication, and ICT). The main findings across the empirical literature show substantial variation in ICT elasticities depending on the methodology. Differences have also been identified in the productivity growth experiences due to ICT between Europe and the United States. Because of variation and the differing impacts seen in the growth experiences of Europe and the United States (van Ark et al 2008), skeptics regarding the role and effect of ICT in reshaping an economy remain to this day.

A number of authors have attempted to account for the differing experiences of Europe and the US. O'Mahony and Vecchi (2005) argue that traditional industry panels failed to find positive contributions because of heterogeneity across industries. Instead the authors pool data for the US and UK and find positive and significant effects of ICT on output growth, as well as excess returns to ICT compared with non-ICT assets. Dahl et al (2011) provide evidence of positive and significant productivity effects of ICT in Europe after 1995, mainly due to advances in TFP. They find that ICT-intensive industries went through a far less dramatic reduction in productivity growth after 1995 than industries that did not use ICT in production. They conclude that the overall slowdown would have been much more dramatic if ICT-intensive industries had not existed in Europe. Vu (2011) conducts three empirical exercises to determine the role of ICT as a source of growth: the first shows that growth in the period 1996-2005 improved relative to the two decades prior; the second identifies a strong association between ICT penetration and growth during this period; and finally the third determines a causal link between ICT penetration and growth using GMM. Interestingly, Vu's (2011) results show that while the penetration of PCs, mobile phones, and Internet users all had a significant causal effect on growth, the marginal effect of Internet user penetration was larger than that of mobile phones, which was larger than that of PCs; however, this marginal effect decreases as the penetration rate increases, suggesting that countries with a lower level of

ICT penetration should be more aggressive in promoting diffusion of ICT, especially in terms of Internet adoption.

According to a meta-analysis of the empirical literature on ICT conducted by Cardona et al (2013), the majority of studies undertaken indicate that the productivity effect of ICT is positive and significant: elasticity estimates range from -0.06 to 0.296 at the firm level, from -0.071 to 0.17 at the industry level, and from -0.013 to 0.162 at the country level. It is important to note that of the 19 firm-level studies, 4 industry-level studies, and 6 country-level studies included in the meta-analysis, only one study at each level reported a negative elasticity. Evidence further indicates that the productivity effect is not only significant and positive, but actually increasing over time. Furthermore, Pohjola (2000:252) previously noted that since the share of investment in GDP for ICT is generally lower than for non-ICT investment, the net social return to ICT capital is much larger: 60-80 percent versus 4 percent, respectively.

Despite the sometimes contradictory results from the experiences of the US and Europe, many academics have continued to tout ICT as the next key to sustainable economic growth and development since the mid-1990s, when productivity growth began to unexpectedly increase (Edquist 2014). Since then, researchers have argued that technological innovations, such as the emergence and utilization of ICT marking the beginning of the digital economy, have helped drive competitiveness and achieve sustained growth, and studies have continuously pointed to this significant effect (Cardona et al 2013). ICT helps create more efficient processes of collaboration, speed information processing and transfer, streamline internal processes, reduce the need for capital through better utilization of equipment, and generally increase communication. Furthermore, ICT lowers the fixed costs of acquiring information and the variable costs of participating in markets, allowing individuals to seek better prices and improve job searches (Cardona et al 2013). It is not difficult to surmise why ICT may have an economic impact, but empirically proving this effect has been a different exercise entirely. Research to date has also focused primarily on the experiences of industrialized countries, while neglecting the potential effects these technologies have in developing economies.

Thus, although investments in ICT are seen as a key driver of productivity growth for developed economies, and research often shows a positive and economically significant relationship, the impact of investments in emerging and developing economies has thus far been weak and ambiguous. Pohjola (2000) finds that, while neither human capital nor information technology seem to have a significant impact on GDP growth in a sample containing both developing and developed countries, investment in ICT does show strong influence for developed (OECD) countries; in fact, the impact is almost as large as for the rest of the capital stock. This may be due to the fact that developing economies lack proper absorptive capacities, such as appropriate human capital levels, and thus gain less than their developed counterparts from investment in ICT (Niebel 2014).

Nevertheless, the World Bank continues to take an optimistic view, stating that "ICTs have great promise to reduce poverty, increase productivity, and boost economic growth..." (World Bank 2012:v). Empirical evidence shows an output of elasticity larger than factor consumption share for ICT, indicating possible spillovers and complementarities of investments in ICT; however, despite small differences between elasticities of developed and developing countries, equality tests cannot be rejected, meaning that a leapfrogging argument still remains questionable (Niebel 2014). Dedrick et al (2013) find that upper-income developing countries have achieved some positive and significant productivity gains from ICT investment in more recent periods as ICT capital stocks have increased and experience has been gained from the use of ICT. This implies that the effect of ICT on productivity is expanding from richer countries to a large group of developing countries as they familiarize with ICT. Dedrick et al (2013) further find that the productivity effects of ICT are moderated by a variety of country factors, such as human resources, openness to foreign investment, increased investment in higher education, and the quality and cost of a country's telecommunications infrastructure, suggesting that effects of ICT depend not only on usage levels but also on the presence of favorable policies supporting ICT use. Thus, as the lowest income countries continue to implement policies supporting ICT, they too can expect productivity gains from investments.

2.2 Telecommunications and Mobile Telephony

With ICT's constantly-evolving definition, one can posit that different facets of ICT could have varying effects on growth, especially in economies with varying states of development. For example, some studies have found inconclusive evidence when focusing on computer penetration, while the same research confirmed positive links between mobile phones and growth (Jacobsen 2003; Vu 2011). Thus, rather than investigating ICT as a whole, it is useful to instead focus on a specific subset of technologies. In an emerging global economy, the ability of the telecommunication sector to provide a network for transferring information has profound implications for growth and development (Madden & Savage 2000). One can imagine that these technologies, because of their low costs and ease of use, may display even stronger economic impacts than their general ICT counterparts. A seminal paper by Hardy (1980), and cited by many ICT studies since, found strong evidence for the contribution of telephones to economic development, before the introduction of potentially higher-impact mobile telephony systems.

Early research into telecommunications focused mainly on infrastructure and investment in infrastructure. Results by Madden & Savage (1998), who examined a sample of transitional economies in Central and Eastern Europe, conclude that telecommunications investment is an important determinant of economic growth after finding a strong positive relationship; however, initial results did not imply a causal relationship and further tests indicated the existence of a bidirectional relationship between telecom investment and economic growth at the aggregate level (Madden & Savage 1998). Results from a follow-up paper by Madden & Savage (2000) suggest a significant positive cross-country relationship between telecommunications capital and economic growth. One of the most important papers in the field, by Röller & Waverman (2001), investigated the effect of telecommunications infrastructure on economic growth using data from 21 OECD countries over a 20 year period, and find evidence of a significant positive causal link, especially when a critical mass of infrastructure is present, which appears to be at a level that is near universal service. Datta & Agarwal (2004) also use data from 22 OECD countries to investigate the long run relationship between telecommunications infrastructure and economic growth. Their results show that telecom is both statistically significant and positively correlated with growth in real GDP per capita.

While early studies tended to focus on OECD data, later studies have expanded focus to low-income countries. Research by Torero et al (2002), using data from 113 countries over a 20-year period, finds a positive causal link between telecommunications infrastructure and GDP; similar to previous research the effect appeared to be non-linear, but unlike other studies this effect was particularly pronounced for countries with a telecom penetration rate of between 5-15 percent. Jacobsen (2003) explores the relationship between telecommunications development and economic growth using data from 84 countries (61 of which are classified as developing) over a period of 10 years. The results indicate that there is a significant correlation between telecommunications and GDP growth, and overall there seem to be larger growth effects from telecommunication development in developing countries than in developed countries. This result contradicts earlier findings and the notion of network externalities put forth by Röller & Waverman (2001), but suggests that indirect effects are more significant in developing countries. Waverman et al (2005) also find that mobile telephony has a positive and significant impact on economic growth, and this impact may actually be twice as large in developing countries compared to developed countries, countering earlier results in the field.

Sridhar & Sridhar (2007) investigate the relationship between telephone penetration and economic growth, and find positive impacts of mobile and landline phones on national output after controlling for capital and labor. They conclude that most of the developing economies have used cellular telephony as a quick and inexpensive way of increasing telecom penetration to leapfrog more traditional ICT infrastructure. Lee et al (2009) examine mobile expansion in Sub-Saharan Africa and similarly find that mobile telecommunications expansion is an important determinant of the rate of economic growth. Moreover, the contribution of mobile cellular phones to economic growth has been growing in importance in the region, and the marginal impact of mobile telecommunication services is even greater wherever landline phones are rare. Most recently, however, Gruber & Koutroumpis (2011) assess the impact of mobile telecommunications on economic growth and find that while mobile telecom diffusion significantly affects both GDP growth and productivity growth, the contribution of mobile telecom infrastructure to economic growth is significantly smaller for low mobile penetration countries than for high ones (0.11 percent versus 0.2 percent contribution to annual GDP growth).

Despite a focal shift towards the experience of developing countries, little consensus has been gained on how the effect of telecoms might differ across countries based on development status. Yet, Hardy's (1980) seminal paper found that the impact of telecoms was greatest in the least developed economies, and it is hard to ignore the experiences of some successful once-developing countries, like Hong Kong, Korea and Singapore, that used telecommunications as a key part of their economic development strategies (Coyle 2005).

2.3 Fixed and Mobile Broadband

In today's connected world, mobile services have become an increasingly important part of how economies work and function. As technology continues to develop, mobile services have the potential to significantly impact economic development through provision of high value 3G and 4G data services. The terms 2G, 3G, and 4G refer to subsequent generations of the underlying wireless network technology that powers mobile broadband networks. While there are a multitude of technical factors that change from generation to generation, the most noticeable change, and the most relevant in terms of this study, is the speed at which data can be uploaded and downloaded by a connected device.

As mentioned previously, 2G networks were the first digital cellular systems, and mobile broadband access was an intermediary step between 2G and 3G. The assumption in this study would be that core 2G networks play an important role, especially in low-income countries. This role would decrease in wealthier countries, as more advanced networks are rolled out and subscribers substitute away from 2G towards 3G and 4G usage. In a similar train of thought, 3G networks should play an important role, but will be most important in countries where access is plentiful and subscribers have the means to connect to these networks; this is most likely to be the case in wealthier countries, and thus an association between 3G/4G in low-income countries might not yet be evident. Nevertheless, in a full-country sample, we expect mobile broadband networks as a whole to play an important role in economic development.

However, the relationship amongst economic growth, 3G and 4G telephony, and mobile data usage has not yet been explored in great detail, due in part to the newness of the field and the unavailability of adequate data. Awareness clearly exists that broadband is associated with a wide array of classes of impact, ranging from strengthened social networks, to increased political activism, to increased spread and decreased control of information. In fact, a series of studies have found a link between mobile penetration and economic growth due to improved communication, social inclusion, economic activity and productivity (Williams et al 2013).

Fixed and wireless broadband share many characteristics of other public infrastructure services, and some research has confirmed positive associations with growth in developing countries. Czernich et al (2011) estimate the effect of fixed broadband infrastructure on economic growth in OECD countries and find that after a country had introduced broadband, GDP per capita was between

2.7 and 3.9 percent higher on average than before introduction, and a 10 percentage point increase in broadband penetration raised annual per capita growth by 0.9 to 1.5 percentage points. While many studies investigate the effect of penetration rates, Rohman and Bohlin (2012) measure the impact of broadband speed on economic growth in OECD countries. They find that a doubling of broadband speed contributes to 0.3 percent growth compared with growth in the base year, further underscoring the the crucial role that fixed and mobile broadband can play.

Although many studies have found a positive relationship between broadband access and economic development, the majority of this research has been restricted to developed economies, likely due to data availability. Yet broadband remains an important ICT across all markets, regardless of development status. In many developing markets, fixed phone lines remain undeveloped or unavailable; thus, mobile services have become the de facto universal providers of communication services. A study conducted by Qiang et al (2009) suggests that broadband's benefits are major and robust for both developed and developing countries, and despite its shorter history, broadband seems to have a higher growth impact relative to other communications technologies, such as fixed and mobile telephony.

Arguably the most extensive study completed to date, Williams et al (2012) explore the impact of mobile telephony in 3 areas: the impact of 3G penetration on GDP growth; the impact of mobile data on GDP growth; and the the impact of mobile telephony on productivity in developing markets. By measuring the impact of substituting basic 2G connections with more advanced 3G connections on economic growth, the authors find that for a given level of total mobile penetration, a 10% substitution from 2G to 3G increases GDP per capita growth by 0.15 percentage points. This implies that for a similar absolute increase in number of 3G connections, countries with a lower 3G penetration experience a higher impact on GDP per capita growth. The increase in 3G networks, supported by proliferation of data-enabled devices allowing Internet connectivity, has also lead to increased data usage. The authors find that a doubling of mobile data use leads to an associated increase in GDP per capita growth of 0.5 percentage points.

While the contribution of mobile telephony and broadband to economic growth appears strong, and materializes in both developed and developing markets (Williams et al 2013), it is important to remember that a number of factors must be accounted for in creating a beneficial broadband environment. Thus, although evidence increasingly points to the positive effects of broadband, and data analysis indicates that economic impact increases with broadband penetration, this impact may also vary by region. This suggests that broadband deployment must be carefully coordinated with research and development policies in order to maximize impact (Katz 2010), and it is increasingly clear that more research is needed to determine the effect of broadband, and how this effect differs across differing economic environments.

2.4 Common Parameters and Methods

Previous research has tended to focus on the effect of ICT and associated technologies on economic development and/or productivity. Some studies, including Datta and Agarhwal (2004) and Williams et al (2012), have used a combination of lagged growth, government consumption/expenditure, population, investment, and trade (proxying for openness of the economy) in order to investigate the effect of a technological factor (such as 3G penetration) on growth. However, ICT studies most often include controls for capital (sometimes broken down into ICT and non-ICT contribution), labor, and human capital. For example, Dedrick et al (2013) use capital stock, disaggregated by the contribution of IT and non-IT capital, and labor to investigate the effect of IT stock on GDP. Niebel (2014) uses capital services, again split into ICT and non-ICT components, labor, and a variable reflecting openness to trade to investigate the effect of ICT capital services on GDP.

More advanced methods, with access to more data of better quality, have endogenized the technological factor, using additional controls in order to do so. Yet, in the aggregate production function, capital, labor, and human capital are generally used to investigate the effect of a technological factor on GDP: Röller and Waverman (2001) use capital and total labor force to investigate the effect of telecom penetration on GDP; Jacobsen (2003) uses capital and human capital to investigate the effect of telecom penetration on GDP; Koutroupmis (2009) uses capital and total labor force to investigate the effect of broadband penetration on GDP; and Gruber and Koutroumpis (2011) use capital and labor to investigate the effect of mobile and fixed lines on GDP. In order to endogenize the technological factor, these studies include variables such as GDP per capita, urbanization, the price of the technological factor, amount of investment in the telecom factor, and urbanization/geographic area in a series of structural equations. However, in general, the aggregate production functions of ICT studies include controls for capital stock/services, labor, and human capital. As such, this study will include a very similar set of controls, to be explained more in Section 3 during a discussion of the methodology.

Panel data is often analyzed using random effects and fixed effects models, and indeed some ICT-based studies, such as Niebel (2014), have employed these methods successfully. However, endogeneity issues, most notably concerns about reverse causality and simultaneity, mean that standard methods of analyzing panel data are likely to be at least somewhat biased. Previous studies in the field have used a variety of methods to tackle endogeneity issues, including two-way FE, GMM, 2SLS and 3SLS, but the most notable studies investigating ICT at the country level employ econometric analysis in the form of simultaneous equations that endogenize the technological factor. This advanced approach estimates production functions in a structural equation model that accounts for different channel effects amongst the variables, endogenizing the technological variable of interest, and in this way explicitly modelling endogeneity and isolating the causal effect for the variable of interest. This is commonly referred to as three-stage least squares (3SLS), a method combining two-stage least squares (2SLS) and seemingly unrelated regression (SUR). This approach has been developed by a number of authors, including Röller and Waverman (2001), Sridhar and Sridhar (2007), Koutroumpis (2009), and Gruber and Koutroumpis (2011).

However, use of the 2SLS and 3SLS approaches to investigate mobile broadband are not currently feasible due to lack of adequate data needed to empirically analyse the set of structural equations that would be set forth. In fact, studies that have used these methods to investigate ICT and telecommunications, such as Sridhar and Sridhar (2007), have also run into data limitations and this problem would likely be compounded when investigating mobile telecommunications because of the novelty of the data. The lack of adequate instruments and other data on mobile broadband (such as price of mobile broadband service, annual for mobile broadband-specific investment, and country revenue per mobile broadband subscription) used to specify the demand and supply equations in the 3SLS simultaneous equations model make analysis with these models extremely difficult, if not impossible at the current moment. However, as data creation and collection continues in this field, this remains an interesting avenue to explore in order to discern the true causal effect of these technologies on economic growth. These issues will be discussed in more detail in the methodology section.

2.5 Contribution of the Study

As shown, agreement has yet to be reached on exactly what effect different ICT technologies have in different economic environments. One can see why mobile telephony, especially when used in combination with mobile broadband, could have strong impacts, especially in low-income countries lacking the traditional public infrastructure systems enjoyed by high-income countries. Developing countries often experience a low telecommunications trap: a lack of networks and access increases costs and reduces opportunities, while resulting low incomes in turn restrict the ability to pay for infrastructure rollout (Waverman et al 2005). It is easy to imagine the effects that cheap technology like this could have for the extremely poor or those living in rural areas, with mobile phones and mobile networks acting as a substitute for fixed lines in poor countries. However, as mentioned, it is clear that more research is needed to determine the exact effects that mobile broadband technology has in varying economic environments, especially as expansion continues into poor and rural areas.

Thus, there are a number of ways in which this research hopes to differentiate itself from previous research in the field. While a wide range of academic studies have been conducted investigating ICT's effect generally on growth or productivity, and some studies have taken a more narrowed scope and focused on the effects of mobile telephone technology and, in rare cases, broadband infrastructure and investment, as far as we are aware there has been very little academic research to date that has looked into the effect of mobile and wireless broadband at a national level. This is due in part to previous lack of data specific to 3G technology and mobile broadband. However, data is now becoming available that can facilitate a more in-depth look at the effect of mobile broadband separate from other ICT. This also allows investigation, albeit still at a fairly high level, into differing effects based on country development status; thus, this is also a goal of the paper as stated in the research question. In a similar vein, as far as we know this is the first paper to use smartphone adoption to investigate the effect of mobile broadband. Unfortunately, currently available data is still not detailed enough to allow for an extremely in-depth analysis of country differences, or to allow for usage of advanced econometric methods that could properly address limitations of the pooled OLS and FE models. However, this study can hopefully still provide insights and conclusions as to the effect of mobile broadband, and attempt to see how estimator coefficients vary for mobile broadband when using different econometric methods.

3 Data and Methodology

In this section, an overview of the methodology undertaken, and methodological issues considered during the study, is presented. Data sources, model specification and empirical implementation are outlined. There exist two different methodological frameworks that are most often employed to explore the economic effect of ICT and related technologies: non-parametric growth accounting and parametric econometric analysis (Edquist 2014). While previous research has established growth accounting frameworks as a reliable approach for testing the contribution of ICT to growth, this method does not allow for the establishment of causal relationships. In addition the interpretation of the measures obtained is affected by the strong assumptions that underpin the theoretical frameworks used.[3] Alternatively, parametric methods are used to estimate production functions, directly estimating output elasticities of input factors from the data generating process without having to assume constant returns to scale and perfect markets. Econometric frameworks use data to test the relationship between growth and other measurable variables that are believed to be important for that growth. Regression equations can be derived from log-linearizing a standard Cobb-Douglas production function, which is then often estimated using panel data, giving the following:

$$\ln Y_{it} = \beta_1 \ln K_{it} + \beta_2 \ln L_{it} + X'_{it} + \epsilon_{it} \tag{1}$$

where Y represents output (typically GDP in country-level studies), K is capital, L is labor, and X represents further controls included in the model specification.

This paper aims to follow in the path of previous parametric approaches while using a slightly augmented methodology, informed by prior research, that will be presented below. The study began by running a pooled OLS regression, along with random effects (RE) and fixed effects (FE) models, explained in more detail in the following subsections. Each of the models was run using time fixed effects, and the appropriate statistical tests conducted to determine which model was most appropriate; regressions were also run after grouping countries into low-, middle-, and high-income

[3] The main critique of growth accounting approaches is the inability to explicitly account for underlying causes of growth, while instead quantifying the proximate sources of growth in a systematic and consistent way assuming constant returns to scale and perfect markets.

categories based on GNI per capita. Finally, a GMM model was employed in an attempt to tackle suspected reverse causality issues.

3.1 Sources of Data

A significant facet of methodology is finding appropriate data for the study. Wireless broadband data was obtained for a number of variables, often segregated by technology generation (i.e. 1G, 2G, 3G, and 4G), using the GSMA Wireless Intelligence Database.[4] Because of the relative novelty of this topic, especially in relation to mobile broadband, data spanning multiple years proved difficult to find. The earliest data in existence comes from the year 2000, arguably the beginning of mobile broadband implementation in the most advanced countries when it comes to mobile telephony. This issue was further complicated when considering that data was available from different starting points across countries due to delayed implementation of more advanced generation mobile broadband systems, often in low-income countries.

A further consideration in regards to data was the scope of the ICT measure used. The most direct implementation of the production function is to use IT capital services as a measure. However, many communication technologies studies at the country level instead choose to use penetration rates. As this study investigates the effect of mobile broadband, variables that describe or proxy for mobile wireless broadband penetration by mobile Internet technology generation (i.e. 2G, 3G, or 4G) were used, such as: unique subscribers by generation, subscriber penetration rate by generation, smartphone adoption rate, or number of smartphone connections. Initial regressions were run using smartphone adoption as a proxy for wireless broadband, under the assumption that a person owning a smartphone is likely to use the features available to access broadband from that phone, thereby accessing 3G and 4G networks. Additional regressions were run using subscription data, disaggregated by technology generation, to confirm or refute the effects seen when using smartphone adoption. The earliest data available for the variables used in this study comes from the year 2007; thus, while the dataset included data for non-wireless broadband control variables from as early as 2000, the final sample used for econometric analysis covers a period of 8 years (2007 to 2014).

Primary data sources for control variables used included the World Bank's World Development Indicators Database (WDI), the Conference Board's Total Economy Database (TED), and the Penn World Tables (PWT). Based upon a standard Cobb-Douglas production function, and previous research in the area of ICT described above, it was decided to include variables in the initial regressions controlling for capital, labor, and human capital. As described in Niebel (2014), when investigating the effect of ICT, capital services are a more appropriate measure to use than capital stocks as cap-

[4] Technology generation refers to generation of the mobile broadband network. Currently, mobile operators in many countries offer 4G services. A higher number generation indicates increased power to send and receive information, often in the form of data, and therefore the ability to achieve higher efficiency through the mobile network. The popularity of 3G networks is due in part to the fact that these were the first networks to allow users access to the Internet over devices like smartphones, while 4G networks contribute faster data transmission speeds and other value added features.

ital services reflect the fact that shorter lived assets (such as computers and smartphones) have a larger return in production and provide more services per unit of stock than long-lived assets. Thus, the differing deprecation rates inherent to different types of capital can be adequately accounted for. The capital services variable was constructed using a capital stock benchmark obtained from the PWT. This benchmark, chosen as the capital stock level for each country in 2005 reflected in 2005 prices, was multiplied by the capital contribution (the sum of the contribution from ICT capital, assumed to be 0 when missing in developing countries, and the contribution from non-ICT capital), obtained from the TED. This allowed calculation of capital services for years 2005 to 2014. For countries where no 2005 benchmark was available, missing values were inserted for all years; thus, there were a number of low-income countries where adequate capital services data was not available. Proxies were used to control for labor and human capital: employment data detailing number of persons employed, obtained from TED, was used to control for labor, while gross enrollment ratios in secondary and tertiary education, obtained from WDI, were used as controls for human capital. While difficult to explicitly measure itself, human capital can be viewed as the target of investment through education and training. Thus, economists have attempted to measure the stock of human capital utilizing school enrollment rates as a proxy (Barro 1991, Barro & Lee 1993). While more preferable measures may exist, they often only cover developed nations; thus, enrollment rates were used in an effort to cover as wide an array of countries as possible.

As the goal of this paper is to compare the contribution of wireless broadband to growth for low-, middle-, and high-income countries, it was necessary to divide the sample into three subsamples. Country groupings were calculated using the World Bank's Atlas Method: low-income countries are defined as those with a gross national income (GNI) per capita of less than 1045 USD; middle-income countries fall between 1045 USD and 12,736 USD; finally high-income countries have a GNI per capita over 12,736 USD.[5] An income grouping was calculated for each country for the year 2007, and this income grouping then used for years 2007 through 2014.

The initial panel dataset consisted of data from 203 countries for the period 2000 to 2014 with a total of 3045 observations. However, empirical analysis was run on a selection of this data due to restrictions of the wireless broadband variables: this final dataset consisted of data from 203 countries for the period 2007 to 2014 with a total of 1624 observations. It is this dataset which is described in the descriptive statistics below. This dataset was strongly balanced.

3.2 Data Exploration

The table below provides a description of the variables used throughout the analysis with corresponding descriptions. This table reports descriptive statistics for the final dataset, covering years 2007 to 2014. Most variables vary greatly between their 5th and 95th percentile (not shown in

[5]Gross national income per capita is defined as GNI, converted to USD using the World Bank Atlas conversion factor instead of simple exchange rates, divided by the midyear population.

the table), rendering confidence that enough variation existed to obtain meaningful results from the regression analysis. A description of all variables included in the dataset, as well as tables of descriptive statistics for the country subsamples, can be found in Appendices B and C.

Table 1: Descriptive Statistics - Full Sample

Variable	N	Mean	SD	Min	Max
GDP (in billion USD)	1466	289	1180	0.142	14,800
GDP growth (%)	1481	3.53	5.79	-62.08	104.49
GDP per capita (USD)	1466	11,332.32	17,328.81	144.90	158,602.50
Capital Services (USD)	944	1,764,320	5,200,827	479	42,300,000
Employment (in thousands)	984	24,029	82,987	68	78,9614
Secondary Enrollment (%)	945	81.04	27.18	7.35	165.58
Tertiary Enrollment (%)	845	39.19	27.55	0.08	117.89
Smartphone Adoption (%)	1616	13.7	15.5	0.05	82.0
Smartphone Connections	1616	4,624,829	26,700,000	45	760,000,000
Subscription % (Total)	1008	44.4	21.2	0.01	95.4
Subscription % (2G)	1003	22.7	13.5	0.25	76.3
Subscription % (3G + 4G)	910	24.3	20.9	0.01	85.9
Subscribers (Total)	1008	9,102,013	36,200,000	199	564,000,000
Subscribers (2G)	1003	4,003,778	18,600,000	652	234,000,000
Subscribers (3G + 4G)	910	5,669,275	23,200,000	42	396,000,000

In the full country sample, mean GDP is approximately 289 billion USD, with a minimum value of 142 million USD (São Tomé and Príncipe in 2007) and a maximum value of 14.8 trillion USD (United States in 2014). Average GDP per capita for the full sample is approximately 11,332.32 USD, with a minimum of 144.90 USD (Burundi in 2007) and a maximum of 158,602.50 USD (Monaco in 2008).

The proxies used to measure for wireless broadband, as our main variable of interest, are also interesting to note. Smartphone adoption, displayed as the percentage share of total connections, can be interpreted as a penetration rate. In the full sample, there is an average smartphone adoption across countries of 14.7 percent, with a minimum of 0.05 percent (Peru in 2007) and a maximum of 82.0 percent (United Arab Emirates and Qatar, both in 2014). There is an average of 4.62 million smartphone connections per country in the full sample, with a minimum of 45 connections (Micronesia in 2007) and a maximum of 760 million connections (China in 2014); however, this data was not used in further regressions aside from checking robustness.

It is also particularly interesting to look at descriptive statistics on the number of subscriptions, disaggregated by generation. In our full sample, the average number of total mobile Internet subscriptions per country is 9.1 million, with an average of 4 million 2G subscriptions and 5.67 million combined 3G and 4G subscriptions. On average, approximately 44.4 percent of unique subscribers utilize mobile Internet, with an average of 22.7 percent subscribing to 2G services and 24.3 percent subscribing to 3G and 4G services. There is a minimum of 0.01 percent total mobile Internet subscriptions (North Korea in 2013 and 2014), 0.25 percent 2G subscriptions (Mauritania in 2010), and 0.01 percent 3G and 4G subscriptions (Guinea in 2011 and North Korea in 2013 and 2014); alternatively, there is a maximum of 95.4 percent total mobile Internet subscriptions (Kenya in 2014), 76.3 percent 2G subscriptions (Kenya in 2013), and 85.9 percent 3G and 4G subscriptions (Japan in 2014).

Here we provide a description of statistics of specific variables of interest for the 3 country subsamples: low-, middle-, and high-income. Tables displaying descriptive statistics for each income group can be found in Appendix C. Patterns for the subsample groups hold as expected: the high-income sample had a higher average level of GDP, GDP per capita, capital services, and gross enrollment ratio at both the secondary and tertiary levels than the middle-income sample, which itself had higher averages in each of these categories than the low-income sample. This trend, interestingly, also holds true for mobile broadband figures. High-income countries have a higher average level of smartphone adoption compared to middle-income countries (27.0 percent versus 10.4 percent), which have a higher average level compared to low-income countries (at 5.6 percent). The maximum value (82 percent) in the full sample occurs in the high-income sample, while the minimum value (0.05 percent) occurs, curiously enough, in the middle-income sample. High-income countries also have the highest average levels of unique mobile broadband subscribers expressed as a percent of total subscribers in both the total and combined 3G and 4G subscription percentage categories, while middle-income countries have the highest average in the 2G subscriber category; low-income countries have, as expected, the lowest averages across all three categories (total, 2G, and 3G+4G). Unsurprisingly, this same trend is reflected in the variable measuring total subscribers as well.

To check whether the variables used in this thesis exhibit a relationship before empirical implementation, it is also important to check corresponding correlations. As can be inferred from the table below, where cross-correlations and corresponding p-values for significance are shown, most variables display a significant correlation. Furthermore, some basic checks can provide confidence that the variables have been encoded correctly. GDP is positively correlated with both capital services and employment, as well as the gross enrollment ratio for tertiary education. Additionally, subscription penetration variables for 2G are negatively correlated with those of 3G and 4G, implying that there is a possible substitution effect as countries move to more advanced networks. Interestingly, the 2G variables display a number of other negative correlations that appear counter-intuitive, which may lead us to question the usefulness of this variable in later analysis.

Table 2: Cross-correlation Table

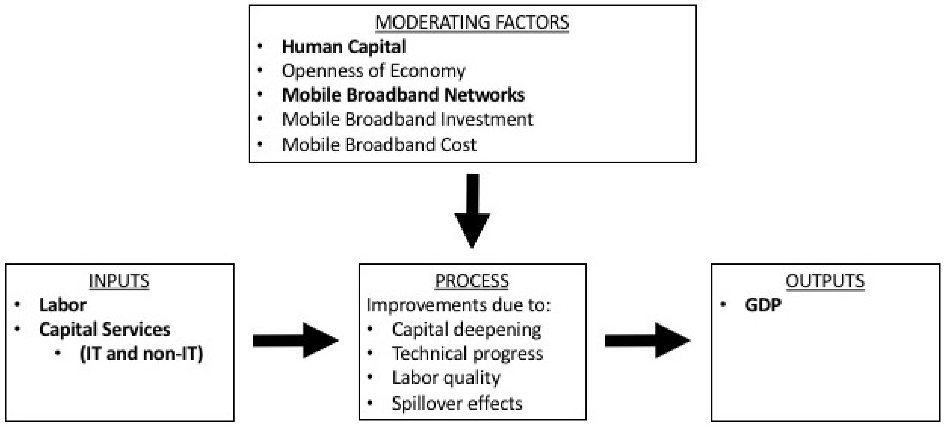
Variables	gdp	gdppc	kservices	lemploy	hktert	smrtadpt	gensub2	gensub34	gensubper2	gensubper34
gdp	1.000									
gdppc	0.260	1.000								
	(0.000)									
kservices	0.912	0.184	1.000							
	(0.000)	(0.000)								
lemploy	0.387	-0.084	0.683	1.000						
	(0.000)	(0.010)	(0.000)							
hktert	0.247	0.457	0.163	-0.112	1.000					
	(0.000)	(0.000)	(0.000)	(0.006)						
smrtadpt	0.214	0.470	0.149	-0.021	0.444	1.000				
	(0.000)	(0.000)	(0.000)	(0.516)	(0.000)					
gensub2	0.326	-0.066	0.616	0.963	-0.038	-0.011	1.000			
	(0.000)	(0.049)	(0.000)	(0.000)	(0.409)	(0.730)				
gensub34	0.736	0.130	0.882	0.691	0.159	0.206	0.599	1.000		
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)			
gensubper2	-0.117	-0.215	-0.058	0.146	-0.080	-0.126	0.174	-0.050	1.000	
	(0.000)	(0.000)	(0.164)	(0.000)	(0.082)	(0.000)	(0.000)	(0.135)		
gensubper34	0.327	0.667	0.255	-0.012	0.623	0.780	-0.002	0.302	-0.325	1.000
	(0.000)	(0.000)	(0.000)	(0.771)	(0.000)	(0.000)	(0.946)	(0.000)	(0.000)	

3.3 Model Specification and Empirical Implementation

The most common starting point for specifying economic models is the standard Solow Cobb-Douglas function $Y = AK^{\alpha}L^{\beta}$ where Y is output, K capital, L labor, capital and labor are weighted by factor elasticities, and A is total factor productivity (TFP). However, necolassical theories have been criticized for failing to properly appreciate the role of technological progress as an input for economic growth, treating it as important but exogenous, leading to the emergence of endogenous growth theories based on the standard Cobb-Douglas production function, but focusing instead on technological progress. In specifying the model used in this paper, we similarly began with the basis of a standard Cobb-Douglas production function that was augmented to accommodate for mobile technologies, following work of Roller & Waverman (2001), Sridhar & Srdihar (2007), Gruber & Koutroumpis (2011), and Niebel (2014).

As mentioned in Section 2, the majority of these ICT-based studies have specified aggregate production functions to include controls for capital stock/services, labor, and human capital. Furthermore, the model is based in part upon a theoretical framework introduced by Dedrick et al (2013), with an adapted version shown below. Variables for capital services and labor, along with proxies for human capital, were included in the analysis, while variables for economy openness (or other institutions) and mobile broadband price/investment were unfortunately not included due to lack of data. This will be explained in further detail when discussing limitations of the study.

Figure 1: Analytical Framework



Note: Variables in bold are included in the quantitative analysis, whereas others are not (due to lack of adequate data)
Source: Adapted from Dedrick et al (2013)

In the standard form, output Y is determined by labor L and capital K, as well as the measure of technological change TFP A. Taking into account country-specific and time-specific effects, we obtain:

$$Y_{it} = A_{it} K_{it}^{\alpha} L_{it}^{\beta} \tag{2}$$

We began with this foundation, but augmented the Cobb-Douglas production function to include factors of potential interest which may play a role in generating increased output, such as wireless broadband utilization, based on the analytical framework above. Variables for capital as measured by capital services, labor as measured by employment, human capital as measured by school enrollment, and mobile broadband as measured by smartphone adoption (as well as number of subscribers with access to 2G, 3G, or 4G networks), and a time trend were included. As previously mentioned, the choice of control variables was also driven in part by data availability. While this specification differs slightly to those used in previous research, it adequately reflects other ICT growth models. The initial specification, including controls commonly used in previous research within the field, was used as a basis, and robustness was later tested by adding additional control variables. Thus, as an initial production function the following was obtained:

$$Y_{it} = f(K_{it}, L_{it}, HK_{it}, MB_{it}, t_{it}) \tag{3}$$

where output Y, as measured by GDP, is determined by capital services K, labor L, human capital HK, and mobile broadband MB. Regression-based output elasticities can reveal the effect that wireless broadband may have on output, and whether these effects differ between the country sub-samples of low-, middle-, and high-income countries.

The regression equations were then derived from log-linearizing the production function, which was then estimated using panel data. Panel data refers to a cross-section of data points repeatedly sampled over time, but one where the same entities, in this case countries, have been followed through the sample period, allowing analysis of more complicated models than in the case of cross-sectional or time-series data handled separately. In panel datasets, the sample N is typically large, while the number of time periods T is short; this is true for the dataset used in this study, with a total of 203 countries observed over a period of 7 years from 2007 until 2014. There are a number of advantages to using panel data to estimate regression coefficients for country analysis: increased precision of estimates; increased variability and decreased aggregation in the sample; increased opportunities to analyze effects over time; and the ability to control for individual country fixed effects. Fixed effects refer to effects that are common to a country across time but may vary across countries at any particular point in time; this becomes useful for omitted variable bias that is fixed over time, as these factors can be controlled for since any change in the dependent variable, GDP, over time cannot be caused by an unchanging omitted variable. The possibility of using data on both time-specific and country-specific effects also allows easier modeling of unobserved heterogeneity, a frequent problem in econometric studies, by demeaning the variables.

A basic linear panel data model for country i in period t is given by:

$$Y_{it} = a_i + \beta' X_{ikt} + e_{it}, \quad i = 1, \ldots, n, \quad t = 1, \ldots, T \tag{4}$$

where Y is the dependent variable for entity i in period t, β' is a vector of k coefficients, X_{it} is a vector of k explanatory variables, and e_{it} is the error term. For the comparison of output elasticities, the augmented Cobb-Douglas production function described above in equation 3 was log-linearized and estimated using a basic linear panel data model, as described in equation 4, as follows:

$$ln(Y)_{it} = a_i + \beta_1 ln(K)_{it} + \beta_2 ln(L)_{it} + \beta_3 ln(HK)_{it} + \beta_4 ln(MB)_{it} + e_{it} \tag{5}$$

with $ln(Y)_{it}$ signifying the logarithmic level of GDP, while $ln(K)_{it}$, $ln(L)_{it}$, $ln(HK)_{it}$, and $ln(MB)_{it}$ signify the levels of the input factors capital, labor, human capital, and wireless broadband (measured by smartphone adoption) respectively in country i at time t; the term a_i indicates country dummies and e_{it} is the general error term. The term a_i is assumed to be constant over time but vary across countries; if this constant were the same across countries, the model could be estimated using ordinary least squares (OLS), leading to consistent and efficient estimates of α and β. However, as these differences are assumed to be fixed constants, application of the fixed effects model is likely most appropriate (ignoring the issue of simultaneity for now). As the panel data for this study consisted of different countries with unobservable differences distinct to each country, OLS was assumed to likely be inefficient. However, with panel data it is possible to control for some types of omitted variables without explicitly observing them by instead observing changes in the dependent variable, in this case GDP, over time. This can be done using either fixed effects or random effects models. These models are explained in more detail below.

Fixed effects (FE) are used when analyzing the impact of variables that may vary over time, and allow exploration of the relationship between independent and dependent variables within a country. Each country has unique characteristics that may or may not influence the independent variables, and the FE model treats the constant a_i in the panel data model as a fixed constant, specific to each country. The fixed effect assumption is that the country specific effect is correlated with the independent variables. Thus, when using FE, any unique aspects within each country that may impact or bias the independent variables are controlled for. The simple panel data model under FE thus becomes:

$$Y_{it} = d_i a_i + \beta X_{ikt} + e_{it}, \quad i = 1, \ldots, n, \quad t = 1, \ldots, T \tag{6}$$

where i is country and t is time, a_i is the unknown intercept to be estimated ($i = 1 \ldots n$, with n country-specific intercepts) and d_i is a dummy variable which is 1 for country i and 0 otherwise (providing country-specific fixed effects), and e_{it} is the error term. Adding country-specific fixed effects to our model, also called a one-way FE model, produces the following:

$$ln(Y)_{it} = d_i a_i + \beta_1 ln(K)_{it} + \beta_2 ln(L)_{it} + \beta_3 ln(HK)_{it} + \beta_4 ln(MB)_{it} + e_{it} \tag{7}$$

with $ln(Y)_{it}$ signifying the logarithmic level of GDP, while $ln(K)_{it}$, $ln(L)_{it}$, $ln(HK)_{it}$, and $ln(MB)_{it}$ signify the levels of the input factors capital, labor, human capital, and wireless broadband (measured by smartphone adoption) respectively in country i at time t; the term a_i indicates country dummies, and e_{it} is the general error term.

Unlike FE, random effects (RE) are used when variation across countries is assumed to be random and uncorrelated with the independent or dependent variables in the model. An advantage of RE is that time invariant variables can be included, whereas these variables are absorbed by the intercept in FE. However, as the model specified above does not include time-invariant controls and we are only interested in those variables that exhibit time variation, FE is likely a more appropriate estimator than RE. The standard method of choosing between FE and RE is to run a Hausman test. FE always give consistent results when working with panel data, but may not be the most efficient model to use. RE on the other hand will give more efficient estimators and should be run if justified. Thus, the Hausman test checks a more efficient model (RE) against a less efficient but consistent model (FE) by testing the null hypothesis that the coefficients estimated by the efficient RE estimator are the same as those of the consistent FE estimator (i.e. that the unique errors e_i are correlated with the regressors). If they are, signified by an insignificant P-value larger than 0.05, then RE can be used. If, however, the P-value is significant then FE should be used.

With both FE and RE, time effects can be added by including a term λ_t in the equation above (as included in the estimation of the Cobb-Douglas production function). Similarly, these time effects can be specified as dummy regressors, with $t-1$ dummies included in the regression. Time-specific fixed effects should be controlled for whenever unexpected variation may affect the dependent variable

Y. Whereas the Hausman test determines if country-specific fixed effects are necessary, necessity of time-specific fixed can be explored by running a joint test to see if dummies for all years are equal to 0: if they are, signified by failure to reject the null hypothesis through an insignificant F value, then no time fixed effects are needed. When both country-specific and time-specific fixed effects are included, a two-way fixed-effect model is employed. The simple panel data model under two-way FE becomes:

$$Y_{it} = a_i + \beta X_{it} + \gamma_t + e_{it}, \quad i = 1, \ldots, n, \quad t = 1, \ldots, T \tag{8}$$

where γ_t represents time-specific fixed effects. Just as the one-way country-specific FE model requires variation over time within each country, the time-specific FE model requires variation over countries within each time period. Adding both time-specific and country-specific fixed effects, employing the two-way FE model, and log-linearizing provides the following:

$$ln(Y)_{it} = d_i a_i + \beta_1 ln(K)_{it} + \beta_2 ln(L)_{it} + \beta_3 ln(HK)_{it} + \beta_4 ln(MB)_{it} + \gamma_t + e_{it} \tag{9}$$

with $ln(Y)_{it}$ signifying the logarithmic level of GDP, while $ln(K)_{it}$, $ln(L)_{it}$, $ln(HK)_{it}$, and $ln(MB)_{it}$ signify the levels of the input factors capital, labor, human capital, and wireless broadband (measured by smartphone adoption) respectively in country i at time t; the term a_i indicates country dummies while γ_t indicates time dummies, and e_{it} is the general error term. The key insight is that as long as unobserved variables do not change over time, then any changes in Y must be due to something other than these fixed characteristics, such as capital services, labor, or wireless broadband. The interpretation would be that for a given country, as the independent variable varies across time by 1 unit (or percent when using logarithmic transformations), then the dependent variable increases or decreases by β units (or percent). The estimator β, called the FE estimator, is computed by demeaning the data, eliminating time-invariant covariates in X along with the country-specific fixed effect a_i and time-specific fixed effect γ_t. If the underlying assumptions of the FE model are fulfilled (again ignoring possible simultaneity issues for now), the FE estimator of β is the best linear unbiased estimator. Cluster-robust standard errors, clustered by country, are reported with FE regressions as Bertrand et al (2004) show that usual standard errors of the FE estimator are drastically understated in the presence of serial correlation, and it is thus always advisable to use cluster-robust standard errors for the FE estimator in order to control for heteroskedasticity and serial correlation.

Log-linearizing the variables also has a number of benefits. First, logarithms have been used frequently throughout general econometric literature, including ICT-based studies. Second, usage of logarithms allowed comparison of the effects of mobile broadband to other control variables, as well as to technological coefficients found in other ICT studies. Interpretation of the coefficients in the log model becomes that of elasticity: on average a percent change in the coefficient of the independent variable of interest is associated with a percent change in the dependent variable.

Econometric analysis was carried out on the full sample as well as for each country subsample (i.e. low-, middle-, and high-income). Thus, for the full sample regressions, three different estimators are presented: the baseline specification is a pooled OLS (POLS) regression, followed by a fixed effects (FE) estimator and a random effects (RE) estimator; the RE and FE models are then also run with time fixed effects. Appropriate postestimation tests were run to determine the most appropriate model. Two-way FE regressions, with both time-specific and country-specific fixed effects, were deemed most appropriate after postestimation tests and only this model was then run for country subsamples, and it is these results that are displayed and analyzed.

3.4 Controlling for Simultaneity

As mentioned previously, one of the main critiques of ICT estimations using FE and RE is that, as ICT can be considered both a driver and a result of growth, this method determines a correlation rather than a causal effect of ICT on productivity. This issue is commonly referred to as simultaneity or reverse causality, and cannot be explicitly addressed in simple regression models. Of course, as this paper aimed to investigate GDP and mobile broadband, it was reasonable to suspect that simultaneity of our independent variable of interest might be an issue: while increases in mobile broadband could lead to increases in GDP, it is equally plausible that increases in GDP actually lead to increases in mobile broadband. In this case, the regression estimates from POLS will be biased (the expected values of the estimate are different from the true values) and/or inefficient (the estimator is less accurate as the sample size increases as compared to an alternative estimator); these issues can also not be appropriately tackled with the FE or RE models used. With the model specifications above, it still must be determined how to properly deal with the issue of simultaneity.

Even though methods like 2SLS may address simultaneity issues, heteroskedasticity may still be an issue. Stiroh (2004) suggests a Generalized Method of Moments (GMM) approach that can be used in the presence of heteroskedasticity. By using GMM, both unobserved heterogeneity and simultaneity are taken into account. Thus, while analysis using 2SLS or 3SLS may not be possible, analysis using GMM techniques developed by Arellano and Bond (1991) is still feasible: a dynamic panel data model is specified and parameters estimated using the Arrelano-Bond GMM estimator. Due to the the presence of endogenous regressors, possibly like that of mobile broadband, static panel data model estimators such as FE and RE estimators are inconsistent. As described, because causality may run in both directions, from mobile broadband to GDP and vice versa, these regressors may be correlated with the error term such that $Ex_{it}e_{it} \neq 0$. To address these issues, one could use GMM as a viable alternative approach.

Unlike static panel data models, dynamic panel data models include lagged levels of the dependent variable as regressors, capturing short run autoregressive behavior of the dependent variable and providing consistent GMM estimators. The estimator takes into account the correlation between previous and subsequent values of growth and, using lagged variables as instruments, is able to properly test for causal effects between the potentially endogenous variable of interest (Roodman

2009), in this case mobile broadband, and the dependent variable. Variables that are suspected to be endogenous are specified as such in GMM-style specifications, and treated similarly to a lagged dependent variable: lagged endogenous variables can serves as instruments in order to address simultaneity. Thus, instead of using only exogenous instruments, lagged levels of the endogenous regressors are added, making endogenous variables pre-determined and, therefore, not correlated with the error term. GMM then transforms the regressors by first differencing, removing the fixed country-specific effect as it is time-invariant. The first-differenced lagged dependent variable is instrumented with past levels to account for autocorrelation. The GMM estimator is consistent, meaning that under appropriate conditions it converges in probability to β as the sample size goes to infinity (Hansen 1982). However, just like 2SLS, it can also be biased because in finite samples the instruments are almost always at least slightly correlated with the endogenous components of the instrumented regressors; nevertheless, the bounds produced by OLS, FE and RE, and the GMM estimators can provide a useful check on results from theoretically superior estimators, such as 3SLS (Roodman 2009).

The Arellano-Bond difference GMM estimator can be seen as part of a broader trend in econometrics towards estimators that make fewer assumptions about the underlying data-generating process and use more complex techniques to isolate potentially useful information. The following assumptions are made about the data-generating process: the process may be dynamic, there may be arbitrarily distributed fixed country effects, some regressors may be endogenous, idiosyncratic disturbances (those apart from the fixed effects) may have country-specific patterns of heteroskedasticity and serial correlation, and these idiosyncratic disturbances are uncorrelated across countries (Roodman 2009). The Arellano-Bond estimator is designed for panels with small time periods and large N samples, such as that used in this study. The equation that was estimated is:

$$\Delta ln(Y)_{it} = d_i a_i + \beta_1 ln(Y)_{i,t-1} + \Delta\beta_2 ln(K)_{it} + \Delta\beta_3 ln(L)_{it} + \Delta\beta_4 ln(HK)_{it} + \Delta\beta_5 ln(MB)_{it} + \gamma_t + e_{it} \tag{10}$$

where $\Delta ln(Y)_{it}$ signifies the change in GDP, while $ln(K)_{it}$, $ln(L)_{it}$, $ln(HK)_{it}$, and $ln(MB)_{it}$ signifying the levels of the input factors capital, labor, human capital, and wireless broadband (measured by smartphone adoption) respectively in country i at time t, and $ln(Y)_{i,t-1}$ signifies the lag of GDP to be used as an instrument. Thus, the Arellano-Bond estimator can be used to investigate causality that was impossible to determine based on the FE or RE models. The issue of reverse causality between smartphone adoption and GDP is then addressed by specifying a dynamic panel data model with the wireless broadband variable of interest as an endogenous variable, and estimating the parameters using GMM techniques.

The methodology concerning GMM estimation closely follows that used by Williams et al (2012) in a study produced by Deloitte for the GSM Association. However, the specification used in this study differs from that used by Williams et al (2012): while the current study embarks using common production function theory as a starting point which is then further informed by previous ICT studies, the former employs a standard endogenous growth model. Furthermore, Williams et al (2012) do not include time dummies in their specification; GMM estimations in this study were run both with and without time dummies, and the differing results were compared to determine the appopriateness of including time-specific fixed effects. Appropriate post-estimation tests were conducted after running Arellano-Bond GMM estimation to further inform as to the appropriateness of the models, as well as to test for autocorrelation of the error term.

4 Results and Analysis

In this section, results from the empirical study and regressions are presented, and an analysis of the results is provided. The results below utilize smartphone adoption as a proxy for wireless broadband, under the assumption that an economically rational person that owns a smartphone is likely to use available mobile broadband services.[6] Results for the full sample for pooled OLS, random effects, and fixed effects regressions, first without time fixed effects and then including time fixed effects, are shown below.

Table 3: POLS, RE, and FE Estimation Results (Full Sample)

Variables	**POLS**	**RE**	**FE**	**RE**	**FE**
Capital Services (*lnK*)	1.028***	0.736***	0.508***	0.772***	0.591***
	(0.084)	(0.061)	(0.178)	(0.056)	(0.169)
Labor (*lnL*)	-0.101	0.327***	0.762***	0.286***	0.705***
	(0.080)	(0.078)	(0.095)	(0.076)	(0.093)
Human Capital (*lnHK*)	-0.036	0.059*	0.006	0.067**	0.013
	(0.081)	(0.033)	(0.028)	(0.031)	(0.028)
Mobile Broadband (*lnSmrtAdpt*)	0.162***	0.010	0.014	0.040***	0.025**
	(0.029)	(0.006)	(0.009)	(0.012)	(0.011)
Constant	13.354***	12.622***	11.974***	12.626***	11.444***
	(0.483)	(0.490)	(1.855)	(0.497)	(1.805)
Time-Specific FE	No	No	No	Yes	Yes
N	566	566	566	566	566
R^2	0.925	0.693	0.745	0.727	0.773

Significance levels: $*$: 10% $**$: 5% $***$: 1%

Note: Cluster-robust standard errors reported

In general, the Hausman test is used to discriminate between using a FE or RE model. The null hypothesis is that both methods of estimation are acceptable, yielding similar coefficients, and thus that the preferred model to use is the RE model, where unique errors are not correlated with the regressors. However, as the Hausman test cannot be run with cluster-robust standard errors, a robust Hausman-like test is run producing a Sargan-Hansen statistic of 101.185 with $Prob > chi^4 = 0.0000$ without time-specific fixed effects, and a Sargan-Hansen statistic of 172.035

[6] If this person had no intention of using these services, or if the services were not available in the first place, they would instead choose to buy, and thus use, a cheaper model of phone that supports basic calling and texting functions but does not allow for Internet connectivity normally available through 3G and 4G networks.

with $Prob > chi^{11} = 0.0000$ with time-specific fixed effects. As both these results are highly significant, we reject the null hypothesis and accept the alternative hypothesis that the FE estimation is acceptable, both with and without time-specific fixed effects. Since the RE estimator is inconsistent, we therefore proceed with using the FE model. We can also test to see if time fixed effects are needed when running the FE model. A joint test to determine if dummies for all years are equal to 0 produces $F(4, 422) = 36.14$, with $Prob > F = 0.0000$; we reject the null hypothesis that coefficients for all years are jointly equal to zero (specifically for years 2008 and 2009), and thus determine that time fixed-effects are necessary, and a two-way FE model is appropriate.

From the results above we can see that across all of the regressions, the control variables that we expect to be significant, namely capital services and labor, are indeed highly significant and, for the most part, have a positive sign as expected. Interestingly, in the POLS regression, labor is significant and has a negative sign; however, as mentioned previously we expect that this estimator is likely biased or inefficient. Furthermore, it is only in the RE regressions that the human capital variable is significant; however, results from the Hausman test indicate that the RE estimator is likely inconsistent, and that the FE estimation is acceptable. Thus, we focus our analysis on the two FE regressions, one without time-specific fixed effects and one with.

As in the POLS and RE regressions, the control variables that we expect to be significant are in fact significant in our FE regressions. As our regression is in log form, interpretation of the coefficients is in terms of elasticities. Both capital services and labor are highly significant, positive, and have coefficients in the reasonable range of what one might expect: from the one-way FE regression, a 10% increase in capital services is associated on average with a 5.08% increase in GDP, while on average a 10% increase in employment is associated with a 7.62% increase in GDP.[7] It seems, at least in the full sample, that labor has a stronger association with GDP than does capital services. However, our main independent variable of interest, mobile broadband, is not significant in the one-way FE model.

However, based on the tests run on RE and FE models, there is reason to believe that the two-way FE model is the most appropriate to use, and thus it is this analysis to which we pay closest attention. The two-way FE regression, accounting for both time-specific and country-specific fixed effects, display similar promising results and the coefficients are, in general, similar to those found in the one-way regression that does not account for time-specific effects. Capital services and labor remain positive and highly significant. Mobile broadband is once again positively signed and significant: a 10% increase in smartphone adoption rate is associated on average with a 0.25% increase in GDP. This is a particularly interesting result, both because it is a quite substantial increase, but also since this result is in line with results and elasticities found from previous ICT studies, while also measuring mobile broadband in a slightly different way. Rather than looking solely at

[7] In the context of this study, a one-way FE regression includes only country-specific fixed effects, while a two-way FE regression includes both country-specific and time-specific fixed effects.

penetration or utilization of 3G and 4G technologies across a country, it appears the same valuable results and insights can be garnered by looking at smartphone adoption, which is arguably easier to measure, and assuming that this is highly correlated with mobile broadband utilization.

In order to determine if the effect of mobile broadband seen in the full sample above differs based on a country's income status, the analysis continued by running regressions after disaggregating countries into low-, middle-, and high-income, based on the World Bank Atlas method. Based on the results of the tests conducted above for the overall sample, the disaggregated regressions proceed only with the two-way FE estimation, using both country-specific and time-specific fixed effects. Results for the full sample, shown in the table above, are displayed in the first column of the table below for comparison.

Table 4: Two-Way FE Estimation Results, By Income Group (Smartphone Adoption)

Variables	**Full Sample**	**Low-**	**Middle-**	**High-**
Capital Services (*lnK*)	0.591***	-0.019	0.673**	0.457***
	(0.169)	(0.262)	(0.316)	(0.158)
Labor (*lnL*)	0.705***	-0.061	0.591***	0.858***
	(0.093)	(0.406)	(0.136)	(0.090)
Human Capital (*lnHK*)	0.013	0.107	0.002	-0.011
	(0.028)	(0.063)	(0.045)	(0.034)
Mobile Broadband (*lnSmrtAdpt*)	0.025**	0.026	0.008	0.019***
	(0.011)	(0.032)	(0.024)	(0.006)
Constant	11.444***	24.139***	11.065***	13.070***
	(1.805)	(4.948)	(3.643)	(1.776)
Two-Way FE	Yes	Yes	Yes	Yes
N	566	126	224	216
R^2 (Within)	0.773	0.815	0.742	0.889

Significance levels: $*$: 10% $**$: 5% $***$: 1%

Note: Cluster-robust standard errors reported

In the two-way FE regression for low-income countries, capital services and labor have a negative sign, indicating a negative effect on growth, while human capital and mobile broadband are positively signed; however, aside from the constant, none of the coefficients are significant and thus we cannot conclude that this is the true effect. The fact that the coefficients in the low-income regressions are insignificant may be due to the small sample size and lack of current data for low-income countries in relation to mobile broadband. Thus, at this point it is difficult to say what effect mobile broadband has in low-income countries in relation to high-income countries: on the one hand a stronger effect could be expected as mobile broadband acts as a substitute for previously lacking public infrastructure, while on the other hand a weaker effect may be seen because necessary capabilities and complementary technologies and services are not in place, as they are in high-income countries, in order to fully extract the benefits of wireless broadband. Alternatively, there may actually be no effect at all.

In the two-way FE regression for middle-income countries, capital services and labor are significant and positive as expected. In the two-way FE regression, a 10% increase in capital services is associated with a 6.73% increase in GDP on average across middle-income countries, while a 10% increase in employment is associated with a 5.91% increase in GDP, indicating that capital services has a slightly stronger association to GDP than capital. Neither human capital nor wireless broadband are significant. As with the effect in low-income countries it is again difficult to say with certainty the exact effect as the coefficient for mobile broadband in the two-way regression, while similar in magnitude to that of our full sample, is no longer significant.

In the two-way FE regression results for high-income countries, our variables of interest are highly significant and have positive signs. Additionally, labor has a stronger association with GDP than capital services. This result seems counter-intuitive as one might posit that the effect of increased labor should be weaker in industrialized and more technologically advanced countries than it would be in low- and middle-income countries, and yet the opposite seems true: increases in labor seem to have the strongest association in higher-income countries, while increases in capital services seem to have a weaker association than in middle-income countries. The coefficients for our wireless broadband variable, as measured by smartphone adoption, are significant and positive. Interestingly, the effect in high-income countries appears to be slightly lower than for that seen in the full sample. In the two-way FE regression, a 10% increase in the rate of smartphone adoption is associated with a 0.19% increase in GDP. Again, the magnitude of this result is in line with results found in previous work looking at the effect of other ICT products on GDP. Elasticity estimates based on country-level ICT studies generally range from 0.012 to 0.15 (Cardona et al 2013), in line with the 0.025 elasticity estimate found in our full sample and the 0.019 estimate found for the high-income sample.

The results seen in the table above, and the lack of significance for low- and middle-income countries, seems to lead credence to the idea that these technologies have stronger impacts in high-income countries, where appropriate public infrastructure is in place and citizens have the necessary capabilities to properly use the technologies available to them, so that these citizens can fully exploit all the benefits of mobile broadband. An important point to keep in mind is that, due to data availability, the high-income countries make up the bulk of those found in the full country sample. As the estimation results for the high-income subgroup seem to follow those of the full sample group fairly closely, especially in terms of significance and sign direction, this could be a situation where the effect seen in our full-country sample is being driven primarily by the experience of high-income countries. However, as the full sample is not composed primarily of high-income countries, this does not seems to be a major concern; this issue will be further explored through further application of different econometric methods. Nevertheless, in the case of the high-income countries, it seems easier to definitively state that an association between mobile broadband and GDP is present (as compared to low- and middle-income countries), though we cannot yet comment on causality and the direction of the effect due to endogeneity issues, specifically simultaneity of GDP and mobile broadband. This discussion will be tackled in later sections.

5 Robustness

5.1 Using Additional Control Variables

Specification of the model used in the previous section, and the resulting control variables that were chosen to be included in the regression specification, were informed by previous research into ICT. However, in order to check the robustness of the results obtained in the previous section, the POLS, RE, and both one-way and two-way FE regressions were run including additional controls. The control variables that were used in the set of regressions included: capital services, employment, rural population, urban population, secondary school enrollment ratio, tertiary school enrollment ratio, government consumption, and trade. Regressions using additional control variables were not run after disaggregating by country group, as this was not of particular interest to the stated research goal of this paper.

Across the set of regressions, the only variable that was consistently significant was capital services. However, post-estimation tests were run and a Sargan-Hansen statistic of 58.044 with $Prob > chi^{17} = 0.0000$, once again indicating that FE estimators were more appropriate than RE, and analysis thus focused on two-way FE results, applying both country-specific and time-specific FE. Using cluster-robust standard errors, capital services, employment, government consumption, and smartphone adoption were all significant: capital services and employment were significant at the 1% level, while government consumption and smartphone adoption were significant at 5% level. None of the other variables included in the regression (population growth, urban and rural population, secondary and tertiary education, and trade) displayed significant coefficients. Specifically, smartphone adoption had a coefficient of 0.022, similar to the coefficient of 0.025 found in the full sample using the simpler model specification. The main takeaway is that the results seem to be robust even when attempting to control for additional factors in the regression. The wireless broadband variable of interest is still significant and shows a similar coefficient as compared to the initial regression using only capital services, employment, human capital, and mobile broadband. Thus, further analysis continued with this simpler model, both founded in economic theory and informed by and based in large part on previous ICT research.

5.2 Using Alternative Mobile Broadband Variables

As the dataset available included other variables that could be used to proxy for mobile broadband (unique mobile broadband subscribers expressed as a percentage of total unique subscribers broken down by technology generation into 2G and 3G+4G, and number of unique mobile broadband subscribers again broken down by technology generation), these variables could be used in further robustness tests to confirm the initial positive association of mobile broadband and GDP.

Regressions were run using only two-way FE, including country-specific and time-specific FE, for the full sample. These regressions were then run again after disaggregating by income group. Two tables are displayed below, one showing results for each of the additional mobile broadband variables.

Looking first at the results below for the full sample, in both full sample regressions the variables that are expected to be significant and positively signed are so, namely capital services, labor, and mobile broadband. However, both of the mobile broadband variables used now disaggregate 2G network usage from more advanced 3G+4G usage; these 3G and 4G networks are those that are typically associated with mobile broadband ability. As we can see, only the 3G+4G variable is significant, while the 2G variable lacks significance. When using unique subscribers as a percentage of total subscribers (seen in the first table), the coefficient for 3G+4G is equal to 0.025, while the coefficient for capital services is equal to 0.33 and for labor is equal to 0.702. This indicates that a 10% increase in the percentage of unique mobile broadband subscribers accessing 3G+4G networks is associated on average with a 0.25% increase in GDP. When using number of unique subscribers (seen in the second table), the coefficient for 3G+4G is equal to 0.024, while the coefficient for capital services is equal to 0.306 and for labor is equal to 0.68. This would indicate that an increase of 10 more 3G+4G subscribers per 100 total subscribers is associated with a 0.24% increase in GDP. The coefficients found using the two different proxies are almost identical, and in line with that found when using smartphone adoption as the proxy, where a coefficient of 0.025 was also found. This is a promising result, and confirms the robustness of the results found in the previous section. However, we would also expect that the 2G variable would show significance across the sample as global build out of advanced mobile broadband 3G and 4G networks has likely not yet reached levels such that 2G networks would fall out of use in low- and middle-income countries. Yet, for reasons unknown this is not the case.

Table 5: Two-Way FE Estimation Results, By Income Group (Subscription as Percentage)

Variables	**Full Sample**	**Low-**	**Middle-**	**High-**
Capital Services (*lnK*)	0.331**	0.014	0.332	0.365**
	(0.167)	(0.388)	(0.266)	(0.162)
Labor (*lnL*)	0.702***	-0.116	0.425**	0.842***
	(0.141)	(0.533)	(0.206)	(0.131)
Human Capital (*lnHK*)	0.011	-0.004	0.004	0.011
	(0.036)	(0.082)	(0.077)	(0.030)
Subscription % (2G) (*lnGenSubPer2*)	0.015	0.036	-0.025	-0.008
	(0.015)	(0.113)	(0.033)	(0.011)
Subscription % (3G+4G) (*lnGenSubPer34*)	0.025***	0.031	-0.006	0.001
	(0.009)	(0.020)	(0.009)	(0.026)
Constant	14.908***	24.701***	16.906***	14.277***
	(1.668)	(6.210)	(3.059)	(1.651)
Two-Way FE	Yes	Yes	Yes	Yes
N	304	63	121	120
R^2 (Within)	0.750	0.750	0.824	0.856

Significance levels: $*$: 10% $**$: 5% $***$: 1%

Note: Cluster-robust standard errors reported

Table 6: Two-Way FE Estimation Results, By Income Group (Number of Subscribers)

Variables	**Full Sample**	**Low-**	**Middle-**	**High-**
Capital Services (*lnK*)	0.306*	0.038	0.335	0.372**
	(0.164)	(0.324)	(0.270)	(0.165)
Labor (*lnL*)	0.680***	-0.208	0.447**	0.845***
	(0.134)	(0.541)	(0.198)	(0.131)
Human Capital (*lnHK*)	0.012	0.009	0.006	0.013
	(0.034)	(0.080)	(0.077)	(0.030)
Subscribers (2G) (*lnGenSub2*)	0.014	0.071	-0.015	-0.009
	(0.014)	(0.081)	(0.031)	(0.011)
Subscribers (3G+4G) (*lnGenSub34*)	0.024***	0.031*	-0.003	-0.002
	(0.008)	(0.018)	(0.009)	(0.025)
Constant	14.802***	23.711***	16.882***	14.305***
	(1.607)	(5.671)	(3.072)	(1.637)
Two-Way FE	Yes	Yes	Yes	Yes
N	304	63	121	120
R^2 (Within)	0.754	0.761	0.821	0.857

Significance levels: $*$: 10% $**$: 5% $***$: 1%

Note: Cluster-robust standard errors reported

Regressions were also run after disaggregating the sample by income group. Patterns of significance across the two sets of regressions are very similar, unsurprising given the similarity in what these two variables measure. In both cases, the low- and middle-income variables for the most part show a complete lack of significance, similar to the results found when using smartphone adoption as the mobile broadband variable. Similar to the initial regressions in Section 4, the lack of significance in the regressions for the low- and middle-income sample groups could be due to the small sample size; in fact these samples are even smaller than those using smartphone adoption as a proxy, as the earliest data for subscribers comes from 2010 (as opposed to 2007 for smartphone adoption). In both high-income samples, capital services and employment are now significant; however, none of the mobile broadband variables are significant (neither the 2G nor 3G+4G) regardless of which proxy is used.

Interestingly, the only case in which the 3G+4G variable showed any significance after disaggregation was when using the number of subscribers variable in the low-income sample. Furthermore, the coefficient, significant at 10% level and equal to 0.031, is quite sizeable. This would indicate that an increase of 10 mobile broadband subscribers per 100 subscribers is associated on average with a GDP increase of 0.31% in low-income countries, larger than the effect found in our full country sample and significantly larger than the coefficient of 0.019 found for high-income countries when using two-way FE. But while this result may seem promising, suggesting a stronger association and possible effect of these technologies in low-income countries, it must be interpreted with a grain of salt as this could be due in part to the very small sample size used for the low-income group. However, this result does provide further justification to look into ways of controlling for simultaneity and other forms of endogeneity by using more advanced econometric methods in order to determine the potentially different effects that these technologies have based on a country's economic environment.

The main takeaway is that the results for the full sample mimic those found in the previous section using smartphone adoption as the mobile broadband proxy, showing that results for the full country sample seem to be robust when adding both additional control variables and using other variables as mobile broadband proxies. The same control variables are significant, albeit at different significance levels, and the variable used to proxy for mobile broadband shows very similar magnitude across all of the two-way FE regression, equal to approximately 0.025 (not counting the 2G variable). Unfortunately, the disaggregated results do not seem to be particularly illuminating, possibly due to the smaller samples sizes. This could be a limitation of data availability: as mentioned previously, data for smartphone adoption and smartphone connections is available from 2007 and beyond, while all subscriber-based data is only available from 2010 and beyond. Thus, using the subscriber data severely restricts the number of observations available in the panel dataset, and may be one reason for the lack of significance after disaggregating by income group. This issue will be further commented on in Section 7 when discussing limitations.

6 Model Extensions

In this section, the model is extended in an attempt to tackle potential endogeneity issues, and the results from the regressions are presented and analyzed. In order to tackle simultaneity that may potentially be present using the two-way FE regressions, Arellano-Bond GMM estimations were employed. With these estimates, causal effects of mobile broadband on GDP can be determined. Results from GMM estimations are displayed in the tables below. Following the methodology of Williams et al (2012), GMM regressions were first run without time-fixed effects: these results for the full sample closely mimicked the results when using two-way FE regressions: capital services, employment, and smartphone adoption were all significant and positively signed. The mobile broadband variable, proxied below by smartphone adoption, is positively signed, though the coefficient slightly lower than that found in initial regressions. A coefficient of 0.017 using GMM, compared to a coefficient of 0.025 using two-way FE estimates in the previous sections, would indicate that a 10% increase in smartphone adoption would lead to a 0.17% increase in GDP on average across the full country sample. In fact, this result is almost equal to that found by Williams et al (2012): testing for the effect of 3G penetration on GDP per capita using a GMM estimation produced a coefficient of 0.015. This suggests two things: first, that the results presented here are robust despite slightly different model specifications and the resulting usage of different control variables, including a different variable to proxy for mobile broadband; secondly, this suggests that smartphone adoption is indeed a good proxy for mobile broadband penetration and usage. The elasticity found for the full sample, with a coefficient of 0.017, is once again in line with those found from previous ICT studies. GMM estimates using the other two available mobile broadband variables showed the same pattern, and the coefficients, both significant at the 5% level, were of similar magnitude, with 0.013 when using number of subscribers and 0.014 when using subscription percentage by technology generation. Post-estimation tests for autocorrelation of the error term were fulfilled in all cases.

Table 7: GMM Estimation Results, By Income Group (Smartphone Adoption)

Variables	**Full Sample**	**Low-**	**Middle-**	**High-**
Lagged GDP (*lag_lnGDP*)	-0.092	0.607***	0.103	-0.354***
	(0.105)	(0.119)	(0.122)	(0.097)
Capital Services (*lnK*)	0.454**	0.190	0.437**	0.582***
	(0.217)	(0.191)	(0.234)	(0.199)
Labor (*lnL*)	0.823***	-0.206	0.686***	1.153***
	(0.114)	(0.291)	(0.147)	(0.143)
Human Capital (*lnHK*)	0.033	0.057	0.040	-0.013
	(0.025)	(0.040)	(0.039)	(0.032)
Mobile Broadband (*lnSmrtAdpt*)	0.017**	0.020	0.016	0.008
	(0.009)	(0.018)	(0.015)	(0.006)
Constant	14.360***	8.977***	10.565***	18.175***
	(1.764)	(3.558)	(3.561)	(2.843)
N	367	77	147	143
Instruments	37	36	35	36
Time FE	No	No	No	No

Significance levels: $*$: 10% $**$: 5% $***$: 1%

Note: Cluster-robust standard errors reported

Unfortunately, the results found when applying GMM estimation without time-fixed effects to disaggregated data were once again not particularly illuminating. While capital services and employment variables are significant when using smartphone adoption as the proxy variable in both the middle- and high-income groups, smartphone adoption itself is not significant. This could again be an issue of limited data: as GMM uses differencing and lagged values of the variables, this restricts the number of observations available for analysis and produces a smaller usable sample size for a technique that ultimately requires more observations. The problem identified in Section 4, where the effect in the full sample is potentially driven primarily by the experience of high-income countries, seems to no longer be applicable. Yet, while significance is no longer seen in the high-income group, promising and insightful results are still available for the full country sample. Based on the GMM estimations, we can say that a causal effect of mobile broadband certainly seems to exist at a national level; however, determining how that effect differs for low-, middle-, and high-income countries does not seem to be possible just yet with the available data.

As we think that it may be necessary to control for time effects, GMM regression were also run with time dummies. Results are shown in the table below. Unfortunately the results obtained when using time FE are not particularly enlightening: results for the full sample look nothing like those found previously, and mobile broadband lacks significance in the full, low-, and high-income samples. Interestingly, mobile broadband is now signficant in the middle-income sample, a group where it has previously never showed significance for the coefficient.

Table 8: GMM Estimation Results with FE, By Income Group (Smartphone Adoption)

Variables	**Full Sample**	**Low-**	**Middle-**	**High-**
Lagged GDP (*lag_lnGDP*)	0.235*	0.565***	0.542***	0.052
	(0.130)	(0.130)	(0.137)	(0.223)
Capital Services (*lnK*)	0.297*	0.169	0.014	0.391**
	(0.172)	(0.210)	(0.177)	(0.173)
Labor (*lnL*)	0.544***	-0.195	0.402***	0.726***
	(0.114)	(0.283)	(0.081)	(0.232)
Human Capital (*lnHK*)	0.030	0.056	0.018	0.002
	(0.022)	(0.035)	(0.045)	(0.023)
Mobile Broadband (*lnSmrtAdpt*)	0.007	0.002	-0.006	0.007
	(0.010)	(0.025)	(0.016)	(0.010)
Constant	10.603***	10.117**	7.672***	13.589***
	(1.781)	(4.687)	(2.925)	(3.637)
N	367	77	147	143
Instruments	42	41	40	41
Time FE	Yes	Yes	Yes	Yes

Significance levels: * : 10% ** : 5% *** : 1%

Note: Cluster-robust standard errors reported

Based on the results above, as well as postestimation tests run after each GMM regression, it seems more appropriate to follow the methodology of Williams et al (2012) and not include time FE in the specification for our GMM regression. Again, this indicates that in our full sample, a causal relationship is found between smartphone adoption, used to proxy for mobile broadband utilization, and GDP. Of course, as mentioned in the methodology, we cannot completely discount possible endogeneity effects, based on the fact that the instruments are almost always at least slightly correlated with the endogenous components of the instrumented regressors in finite samples. Thus, while the GMM estimates above may still be slightly biased, the results do seem to point to a causal effect. There are a number of channels in which this effect could manifest, some of which have been researched heavily and mentioned in previous sections; however, it is outside the scope of this thesis to speculate as to the exact mechanisms through which mobile broadband impacts economic development.

Perhaps a more interesting result that arises from the series of regression models used in this thesis is that, even though we assumed that our initial results were likely biased because of simultaneity issues, our two-way FE regression does not produce drastically different estimates than when using GMM techniques. This is in line with the findings of Tambe and Hitt (2012): GMM estimators that account for endogeneity are often only about 10% lower than unadjusted estimates in ICT-based studies. This suggests that the effects of endogeneity on ICT studies are generally quite small, and this seems also to be the case for this study. Evidence regarding the inclusion of fixed effects is much clearer: estimation results are often much more conservative, and this may justify GMM regressions without fixed effects over time. Of course, caution must be used with each new study, model, and ICT variable used. However, results seem to suggest that simpler panel data models, unable to control for possible endogeneity, can still provide extremely insightful results. This could be key for researching country groups that are often characterized by low quality data. As more data becomes available, this may be particularly useful for studying low- and middle-income countries, where the substantial data needed to build structural equation models will likely still be hard to find.

7 Discussion

7.1 Summary of Results

Through the course of this study, we moved from simpler econometric models that could not adequately control for potential simultaneity issues to using GMM estimations that could. Across the many models used and regressions run, results for the full sample always seemed promising, with the coefficient estimates for mobile broadband displaying significance and similar magnitudes across the estimators, despite the usage of different variables to proxy for the mobile broadband effect. Furthermore, it seems that when investigating the full country sample, an effect of mobile broadband is clearly present. As expected, capital services and employment always had positive significant effects on GDP, while the effect of human capital did not seem to have as consistent an effect; insignificance of human capital could be a problem with how this variable was proxied, and perhaps a better proxy would show more consistent significance.

Potentially more exciting is that the elasticities for mobile broadband found in this study are in line with elasticities found in previous ICT studies. Based on the elasticity found using GMM estimation, which we have reason to believe is the least prone to simultaneity issues, results suggested that for a given level of smartphone adoption, across the entire sample of countries considered, if countries had a 10% higher level of smartphone adoption between 2007 and 2014, they would have experienced an increase in the average annual growth rate of GDP by 0.17 percentage points. Unfortunately, the results for samples after disaggregating by income levels are less consistent across estimators and the effects thus harder to state with certainty, likely because of data issues. This is especially true for low- and middle- income countries.

Another exciting insight to come out of this study is the difference in coefficient estimates found when employing different estimation methods, using POLS, RE, FE, and GMM. Since panel data was being used for analysis, POLS and RE estimators were thought to likely be biased; analysis proceeded with one-way and two-way FE, with postestimation tests confirming that two-way FE were most appropriate. It was this model that the majority of the analysis in this thesis was based. Consequently, reverse causality concerns prompted the usage of GMM estimation. Yet, using both two-way FE and GMM estimation produced similar results, in line with previous research into the role that reverse causality plays in ICT-based studies. While each study should confirm this finding independently, it seems that simple FE models can still be useful for providing initial insights, especially when large amounts of data needed to specify structural equations or instrument with GMM are not available. This could be particularly useful for future research focusing on low-income countries, where data availability may continue to play a role in a study's feasibility.

One could argue that the use of smartphone adoption as a proxy variable is quite innovative: rather than capturing the effect of a specific network generation, we can measure the effect of mobile broadband across multiple networks (both 3G and 4G). To our knowledge, investigation into the effect of mobile broadband has never been studied in this manner. Furthermore, to our knowledge this is the first study to investigate mobile broadband using subscriber-based data rather than connections, as subscriber data more accurately reflects individual usage and penetration rates. While research would be needed to confirm, one could also reasonably assume that the magnitude of any effect that is present may only get stronger as network speeds increase, from 3G to 4G to 5G, and receiving technology in phones becomes better.

Thus, while it is extremely promising that mobile broadband seems to have such a consistent and strong effect, and the magnitude of this effect is in line with those of previous studies looking at other information-based technologies, it is still quite difficult at this point to determine if this effect differs based on a country's development status. Based on the results of the two-way FE and GMM estimations, we can say that a causal effect of mobile broadband certainly exists at a national level on average across the entire country sample; the two-way FE estimation seems to suggest an effect in high-income countries as well, though this cannot be confirmed using GMM. Determining how the effect differs for low-, middle-, and high-income countries does not seem to be possible just yet with the available data. But while nothing can be said conclusively, there are subtle suggestions in the results that mobile broadband may have a stronger effect in low-income countries. This provides strong justification for further research, especially looking at the experiences of low- and middle-income countries in using these technologies, as standardized data is collected over more years and for more countries.

7.2 Validity and Limitations

Internal Validity. In any academic study which makes statistical inferences, internal validity is an important issue to consider. Potential threats to internal validity include omitted variable bias (OVB), incorrect model specification, measurement errors, sample selection bias, and simultaneity.

The potential for OVB always exists, and there may of course be variables that could impact the dependent variable GDP and be correlated with the regressors used, in which case the estimates described could be biased. However, it is believed that controlling for time-invariant effects via a FE model, with the addition of both time-specific and country-specific fixed effects, deals with OVB to a large extent; furthermore, employment of the Arellano-Bond GMM difference estimator also accomplishes this. Nevertheless, we cannot be certain that the model is not subject to OVB.

The functional form of the model appears to be correctly specified: the basis of the model is founded in economic theory, and further informed by models used in previous ICT research. Measurement error does not seem to be a significant issue in our research considering that data was gathered from trusted international agencies including the World Bank, the Conference Board, and the GSM Association. Nevertheless, collection of data about emerging technologies, and the new methods employed to collect this data, can be a cause for concern; this is especially true when dealing with data in developing environments, where data collection methods may not be as standardized as in industrialized countries. In a similar frame of thought, sample selection bias could have occurred in the process of excluding countries due to lack of data. As mentioned, there may be reason to believe that the experience of high-income countries drives the results seen in the full country sample, potentially since these are the countries for which the best data exists. However, this is believed to be a minor issue and should not severely distort results for the full sample, especially considering the broad range of countries in the sample, and the fact that low- and middle-income countries make up half of those countries included.

A more serious issue when investigating the impact of any ICT on economic development is the possibility of reverse causality or simultaneity bias. For example, even though it is believed that mobile broadband impacts GDP, it could also be the case that increases in GDP instead lead to increases in mobile broadband. Previous studies suggest that there may be truth to both mechanisms. Thus, reverse causality can be an issue in our research. It is for this reason that GMM estimation was explored in order to properly address possible simultaneity bias, and while results seemed to show that simultaneity may be an issue, the change in elasticities was not drastic. Nevertheless, simultaneity is still an issue to consider, even when using GMM estimations. Nevertheless, it appears that the internal validity of this study is high. Yet, the possibility of potential omitted variables and reverse causality bias cannot be rejected.

Country Grouping. The country grouping used is at the core of the work of this paper. However, it does come with a few minor drawbacks, specifically in restricting the sample of low-income countries available for analysis. The method used in this study, by defining income groups based on the World Bank's World Atlas method, was a significant limitation when investigating differing effects by country income status. Very few observations were left in the low-income group, which made analysis of this group extremely difficult and any potential results questionable due to the very small sample size. Future research may choose to disaggregate countries using different measures, such as HDI, or creating fewer country groups. Analysis could proceed after disaggregating countries into developed and developing groups; in fact, this was attempted for some of the regressions run in this paper but did not produce any interesting results (i.e. variables were not more significant after combining low- and middle-income groups than they were when these groups were separated).

Variables Employed. Unavailability of data in regards to some controls, especially for low-income countries, meant that it was difficult to include these factors in the model specification. For example, inclusion of a variable to measure quality of institutions would have been reasonable, and future research should consider an institutional variable in the model specification, especially in relation to how the interaction between mobile broadband and quality of institutions affects growth in low- and middle-income countries. Similarly, the level of investment in mobile broadband networks within a country may be an important factor to consider, and one that would be essential for 3SLS analysis.

One may also question the suitability of smartphone adoption as a proxy, and how adequately this proxy actually measures mobile broadband usage. This was the justification for checking robustness of the results using other mobile broadband variables that more typically resembled penetration rates, but unfortunately had shorter measurement periods and thus fewer observations. Additionally, subscriber data was used in this study as it is a more accurate reflection of technology penetration than connection data: connections differ from subscribers such that a unique subscriber can have multiple connections. Using subscriber market penetration rates based on technology generation (i.e. 2G, and 3G/4G) would be ideal, but this data is not yet publicly available, and likely only covers a very short time period. Usage of variables measuring connections, for which longer-term data is often easier to find, could be an alternative in order to further investigate the differing effects based on development status, though this may also lead to greater distortions (for example, having multiple connections is quite common in some low-income countries).

Nonetheless, use of smartphone adoption as a proxy for mobile broadband seemed to be a good choice at the current moment, as the time horizon for this variable was longer than other available variables, and robustness checks seemed to confirm this choice. Furthermore, as mentioned this appears to be the first study to use smartphone adoption rates to investigate mobile broadband as far as we are aware. Yet while the initial assumption that an economically rational person would only spend extra income to purchase a smartphone if they also had the ability to use a mobile broadband networks seems reasonable, there may still be important aspects linked to usage (such as amount of data used or what the data is used for) that are not reflected in the smartphone adoption rate, but could be important factors to consider.

Time Horizon and Data Availability. In the scope of ICT research, mobile broadband data is still relatively new, with the earliest data on mobile broadband penetration rates only 10 years old. The newness of this data still does not allow for application of more appropriate advanced methods, such as 3SLS, to properly investigate causality. This problem is even more evident for low- and middle-income countries, where income levels have historically restricted purchasing of phones capable of accessing mobile broadband (i.e. smartphones); furthermore, prices for purchasing data packages can also be prohibitively high in some countries. This combination of factors leads to a lack of data in certain environments. As network expansion continues, and prices decrease as competition increases, creation and collection of data will be a crucial next step for future research. Future research will undoubtedly have access to better data, both in terms of quantity and quality, and research undertaken in 5-10 years will likely provide more extremely interesting results.

7.3 Future Research

As stated, there is clearly a need for better data, both in terms of quality and quantity, in order to differentiate an effect based on a country's development status. However, this is likely an issue that can only be solved with more time and focus on proper data collection in low- and middle-income settings. Performing a more advanced analysis some years from now, and possibly including data for regressors that currently do not exist, would provide valuable additional insights for three primary reasons. First, due to the relative novelty of mobile broadband networks, adequate data is really only available from the year 2005 onwards. A panel with increased time periods will provide valuable additional insights, especially for studies attempting to differentiate effects based on country development status. Understanding if, how, and why results differ in five or ten years would be very interesting. Second, a longer time horizon could provide valuable information about the lifecycle of these networks, and if effects remain constant over the usable life of a network before a more advanced system is rolled out, or if the strongest effects are experienced during the initial introduction of a newer and faster network. Again, one could assume that the answer to this question depends heavily on each country, and the capabilities of the users within that country. Third, we might expect to see time lags associated with these technologies, as productivity initially decrease after introduction of the technology before eventually increasing. A longer time period could be used to investigate if any time lags exist for mobile broadband effects: perhaps the benefits of a technology are not seen until the citizenry has had time to properly learn and adjust to the technology's use, and apply that technology to day-to-day life. This could be especially true as advanced technologies, like smartphones and mobile broadband allowing Internet connectivity, become increasingly available to the masses as prices decrease.

Additionally, as data continues to be collected and created, application of more advanced econometric techniques, such as 2SLS and 3SLS, will become possible. However, this will also require data that currently exists only for a very select few countries, such as revenue per broadband subscriber. Additionally, while an effect seems to be present, future research should explore how different data usage patterns may alter this effect. For example, the different ways in which data is used from country to country may have important implications: while the opportunity to use data exists in both South Africa and Japan, the ways that data is being used can be very different (video streaming vs. mobile banking vs. simple web searches) and these differences might have profound effects. Indeed, the Ericsson Mobility Report (2015) concluded that large differences exist in subscribers' data consumption patterns between networks, markets, and subscriber segments. A number of factors, such as data plans, device capabilities and overall network performance, impact data consumption per subscriber. One can reasonably assume that differences in data usage could likely lead to different effects in productivity and growth. Informed insights into the subtle ways that differing user patterns can drive a country's economic path will inform not only technology companies, but can have huge impacts on government policy and resource/budget allocation.

As these technologies, their complementary applications, and the ways in which they influence our lives become more widespread, one can think that mobile broadband might also have impacts in areas outside of economic development. As previous studies have pointed out, investigating how mobile broadband affects other variables that are deemed good for growth, such as trade and foreign investment, may be a worthwhile endeavor. Research into how mobile broadband affects quality of life indicators, such as life expectancy, infant mortality and illiteracy, would also be an extremely interesting avenue of research, especially given the potential for these technologies to have impacts in low-income settings. Of course, correlations must again be treated with great caution given the possible existence of simultaneity and omitted variables. However, research into the effect of mobile broadband on health and education could help drive further expansion of 3G and 4G networks into rural areas still lacking service, as well as development of applications designed around areas like health and education, specifically for low-income target markets. Linked to ICT's potential as a GPT, the potential for trickle down effects from these technologies in poor and rural areas could further direct both technology research and government policy.

8 Conclusion

In this thesis, we set out to investigate mobile broadband and the economic impact that these technologies have had. This is a crucial topic in light of the rapid expansion of mobile telephony and mobile broadband. Yet, as far as we are aware, very little research has focused on mobile broadband; thereby, this thesis seeks to contribute to the literature that researches the relationship between economic change and mobile networking technologies.

The basic findings are in line with those from previous ICT-based studies in the sense that mobile broadband is observed to have a positive association with economic development. Using a variety of econometric methods that increasingly attempted to tackle reverse causality issues, this association was explored and repeatedly confirmed when using a sample containing a full range of countries. Under the assumption that GMM is the most appropriate model, we can say that a causal effect exists between mobile broadband and economic development: these results suggested that for a given level of smartphone adoption, a 10% higher level of smartphone adoption between 2007 and 2014 would have lead to an increase in the average annual growth rate of GDP by 0.17 percentage points. Even more interesting, the elasticities found using two-way fixed effects (FE) and generalized method of moments (GMM) models were not drastically different: in this regard, simpler panel data models seem to give insightful results, albeit with slightly overstated coefficients, despite endogeneity concerns. This could prove useful when researching areas that may lack quality data. A second goal of this thesis was to investigate if the impact of mobile broadband differed based on a country's development status. However, at the current moment little can be said conclusively. While initial results suggested a positive association in high-income countries, this relationship could not be confirmed with GMM methods; furthermore, definitive conclusions could not be made about the experiences of low- and middle-income countries using any of the available methods, likely due to lack of data and small sample sizes. However, there are suggestions in the results that point to the potential for strong effects in low-income countries.

Contemplating the implications of these results, a number of potential future actions come to mind. Firstly, while an economic effect is indeed intuitive and seems to be evident from a full country sample, more research using more substantial data is clearly needed to determine how this effect could potentially change from country to country, based on a variety of factors. This will help to further inform policy decisions, and future broadband network roll out. Secondly, research into complementary aspects is important, both in terms of how these variables (such as health and education) facilitate utilization of mobile broadband by individuals and also if/how mobile broadband impacts these quality of life indicators.

To conclude, we call for more research on the relationship between mobile broadband and economic development. Although the results presented in this thesis point towards a positive relationship using a sample of both developing and developed countries, it is believed that more research with a regional and/or country level, using both a qualitative and quantitative perspective, may not only lead to more clarity but also has the potential to direct policies that lead to greatly improved lives in communities around the world.

9 References

1. Arellano, M & S Bond. (1991). “Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations.” *Review of Economic Studies*, 58(2): 277–297.
2. Barro, R. (1991). “Economic Growth in a Cross Section of Countries.” *The Quarterly Journal of Economics*, 106(2): 407-443.
3. Barro, R & JW Lee. (1993). “International comparisons of educational attainment.” *Journal of Monetary Economics*, 32(3): 363-394.
4. Bertrand, M et al. (2004). ‘How Much Should We Trust Differences-In-Differences Estimates?” *The Quarterly Journal of Economics*, 119(1): 249-275.
5. Bresnahan, T & M Trajtenberg. (1995). “General Purpose Technologies: Engines of Growth?” *Journal of Econometrics, Annals of Econometrics*, 65(1): 83-108.
6. Cardona, M et al. (2013). “ICT and productivity: conclusions from the empirical literature.” *Information Economics and Policy*, 25(3): 109-125.
7. The Conference Board. (2015). The Conference Board Total Economy Database. Available from: <http://www.conference-board.org/data/economydatabase/>.
8. Coyle, D. (2005). “Overview.” *Africa: The Impact of Mobile Phones*, Vodafone Policy Paper Series Volume 2, March 2005, pages 3-9.
9. Crandall, R & H Singer. (2010). “The Economic Impact of Broadband Investment.” *Study for Broadband America*, 1-57. Retrieved from Internet Innovation Alliance website: <http://internetinnovation.org/files/special-reports/Economic_Impact_of_Broadband_ Investment_Broadband_for_America_.pdf>.
10. Czernich, N et al. (2011). “Broadband Infrastructure and Economic Growth.” *The Economic Journal*, 121(552): 505-532.
11. Dahl, C et al. (2011). “ICT and Productivity Growth in the 1990’s: Panel Data Evidence on Europe.” *Empirical Economics*, 40(1): 141-164.
12. Datta, A & S Agarwhal. (2004). “Telecommunications and economic growth: a panel data approach.” *Applied Economics*, 36(15): 1649-1654.
13. Dedrick, J et al. (2013). “Information Technology and Productivity in Developed and Developing Countries.” *Journal of Management Information Systems*, 30(1): 97-122.
14. Edquist, H. (2014). “The Economic Impact of ICT – A Research Overview.” Ericsson Internal Report, 1-33.
15. Ericsson. (2015). “Ericsson Mobility Report.” Stockholm, Sweden: Ericsson, 2015.
16. Feenstra, R et al. (2015) “The Next Generation of the Penn World Table.” forthcoming *American Economic Review*. Available from: <www.ggdc.net/pwt>.
17. Gruber, H & P Koutroumpis. (2011). “Mobile telecommunications and the impact on economic development.” *Economic Policy*, 26(67): 387-426.
18. GSM Association. (2015). GSMA Wireless Intelligence Database. Available from: <http://gsmaintelligence.com/>.
19. Hansen, LP. (1982). “Large Sample Properties of Generalized Method of Moments Estimators.” *Econometrica*, 50: 1029–1054.
20. Hardy, A. (1980). “The role of the telephone in economic development.” *Telecommunications Policy*, 4(4): 278-286.
21. ITU. (2015). “ICT Facts & Figures: The World in 2015.” Geneva, Switzerland: International Telecommunications Union, 2015. 1-6.
22. Jacobsen, K. (2003). “Telecommunications - a means to economic growth in developing countries?” *Report produced for the Chr. Michelsen Institute.* Bergen: CMI, 2003. 1-53. Retrieved from CMI website: <http://www.cmi.no/publications/publication/?1732=telecommunications-a-means-to-economic-growth-in>.
23. Katz, R. (2010). “The Impact of Broadband on the Economy: Research to Date and Policy Issues.” 10th Global Symposium for Regulators. Dakar, Senegal. 10 November 2010. Presentation.
24. Koutroumpis, P. (2009). “The economic impact of broadband on growth: A simultaneous approach.” *Telecommunications Policy*, 33(9): 471-485.

25. Lee, S et al. (2009). "Telecommunications and Economic Growth: An Empirical Analysis of Sub-Saharan Africa." Retrieved from SSRN website: <http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1567703>.

26. Madden, G & S Savage. (1998). "CEE telecommunications investment and economic growth." *Information Economics and Policy*, 10(2): 173-195.

27. Madden, G & S Savage. (2000). "Telecommunications and economic growth." *International Journal of Social Economics*, 27(7/8/9/10): 893-906.

28. Niebel, T. (2014). "ICT and Economic Growth – Comparing Developing, Emerging and Developed Countries." (Discussion Paper No. 14-117). Retrieved from ZEW Centre for European Economic Research website: <http://ftp.zew.de/pub/zew-docs/dp/dp14117.pdf>

29. OECD. (2009). "Guide to Measuring the Information Society." Paris, France: OECD, 2009.

30. O'Mahony, M & M Vecchi. (2005). "Quantifying the Impact of ICT Capital on Output Growth: A Heterogeneous Dynamic Panel Approach." *Economica*, 72(288): 615-633.

31. Pohjola, M. (2000). "Information Technology and Economic Growth: A Cross-Country Analysis." *Information Technology, Productivity, and Economic Growth: International Evidence and Implications for Economic Development*. Ed. M. Pohjola. Oxford: Oxford University Press, 2001. 242-256.

32. Qiang, C et al. (2009). "Economic Impacts of Broadband." *2009 Information and Communications for Development: Extending Reach and Increasing Impact*. Washington, DC: World Bank, 2009. 35-50. Retrieved from World Bank website: <http://siteresources.worldbank.org/EXTIC4D/Resources/IC4D_Broadband_35_50.pdf>.

33. Rohman, I & E Bohlin. (2012). "Does Broadband Speed Really Matter for Driving Economic Growth? Investigating OECD Countries." Retrieved from SSRN website: <http://ssrn.com/abstract=2034284>.

34. Roodman, D. (2009). "How to do xtabond2: An introduction to difference and system GMM in Stata." *The Stata Journal*, 9(1): 86-136.

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

36. Solow, R. (1957). "Technical Change and the Aggregate Production Function." *Review of Economics and Statistics*, 39(3): 65–94.

37. Solow, R. (1987). "We'd Better Watch Out." *New York Times Book Review*, 12 July 1987, page 36.

38. Spiezia, V. (2012). "ICT-investments and productivity: Measuring the contribution of ICTs to growth." *OECD Journal: Economic Studies*, 2012(1): 199–211. Retrieved from OECD website: <http://dx.doi.org/10.1787/eco_studies-2012-5k8xdhj4tv0t>.

39. Sridhar, K & V Sridhar. (2007). "Telecommunications Infrastructure and Economic Growth: Evidence from Developing Countries." *Applied Econometrics and International Development*, 7(2): 37-61.

40. Stiroh, K. (2004), "Reassessing the Impact of IT in the Production Function: A Meta-Analysis." Working Paper. New York, NY: Federal Reserve Bank of New York.

41. Tambe, P & L Hitt. (2012). "The Productivity of Information Technology Investments: New Evidence from IT Labor Data." *Information Systems Research*, 23(3-1): 599-617.

42. Torero, M et al. (2002). "Telecommunications Infrastructure and Economic Growth: A Cross-Country Analysis." Retrieved from Editorial Express: <https://editorialexpress.com/cgi-bin/conference/download.cgi?db_name=lasm 2003&paper_id=159>.

43. van Ark, B et al. (2008). "The Productivity Gap between Europe and the United States: Trends and Causes." *Journal of Economic Perspectives*, 22(1): 25-44.

44. Vu, K. (2011). "ICT as a source of economic growth in the information age: Empirical evidence from the 1996–2005 period." *Telecommunications Policy*, 35(4): 357-372.

45. Waverman, L et al. (2005). "The Impact of Telecoms on Economic Growth in Developing Countries." *Africa: The Impact of Mobile Phones*, Vodafone Policy Paper Series Volume 2, March 2005, pages 10-23.

46. Williams, C et al. (2012). "What is the impact of mobile telephony on economic growth?" *Report*

produced for the GSM Association. London: Deloitte LLP, 2012. 1-29. Retrieved from GSMA website:
<http://www.gsma.com/publicpolicy/wp-content/uploads/2012/11/gsma-deloitte-impact-mobile-telephony-economic-growth.pdf>.

47. Williams, C et al. (2013). "The Economic Impact of Next-Generation Mobile Services: How 3G Connections and the Use of Mobile Data Impact GDP Growth." Global Information Technology Report 2013, 77-80.

48. World Bank. (2012). "Information and Communication Technology (ICT) for greater development impact : World Bank Group strategy for ICT." Washington, DC: World Bank, 2012. 1-66.

49. World Bank. (2014). World Development Indicators. Available from: <http://data.worldbank.org/data-catalog/world-development-indicators>.

10 Appendices

10.1 Appendix A: List of Abbreviations

2G	second-generation wireless telephone technology
2SLS	two-stage least squares
3G	third-generation wireless telephone technology
3SLS	three-stage least squares
4G	fourth-generation wireless telephone technology
GPT	general purpose technology
FE	fixed effects
GDP	gross domestic product
GNI	gross national income
GMM	generalized method of moments
ICT	information and communications technology
ITU	International Telecommunication Union
OECD	Organisation for Economic Co-operation and Development
OLS	ordinary least squares
OVB	ommitted variable bias
POLS	pooled ordinary least squares
PWT	Penn World Tables
RE	random effects
SUR	seemingly unrelated regression
TED	Total Economy Database
WDI	World Development Indicators
WPIIS	Working Party on Indicators for the Information Society

10.2 Appendix B: Variable Overview

Variable	Name	Description
GDP[1]	*gdp*	Sum of gross value added in constant 2005 USD by all resident producers in the economy
GDP growth[1]	*gdp_grwth*	Annual percentage growth rate of GDP at market prices based on constant local currency
GDP per capita[1]	*gdppc*	GDP in constant 2005 USD divided by midyear population
Capital Services[4]	*kservices*	Capital-income weighted average of the growth rates of each asset
Employment[2]	*lemploy*	Persons employed (in thousands of persons)
Secondary Enrollment[1]	*hksec*	Ratio of total enrollment in secondary education, regardless of age, to the population of the age group that corresponds to the level of education shown; secondary education completes provision of basic education that began at primary level
Tertiary Enrollment[1]	*hktert*	Ratio of total enrollment in tertiary education, regardless of age, to the population of the age group that corresponds to the level of education shown
Total Population[1]	*pop*	Midyear count of all residents regardless of legal status or citizenship
Urban Population[1]	*pop_urb*	People living in urban areas as defined by national statistical offices
Rural Population[1]	*pop_rur*	People living in rural areas as defined by national statistical offices
Government Consumption[1]	*govcons*	General government final consumption expenditure includes all government current expenditures for purchases of goods and services (including compensation of employees)
Trade[1]	*trade*	Sum of exports and imports of goods and services measured as a share of gross domestic product

Smartphone Adoption[3]	*smrtadpt*	Smartphone connections expressed as a percentage share of total connections; a smartphone is defined as a mobile handset enabling advanced access to internet-based services with computer-like functions
Smartphone Connections[3]	*smrtconn*	Unique SIM cards (or phone numbers where SIM cards are not used) that have been registered on the mobile network and are used in a smartphone device at the end of the period; a smartphone is defined as a mobile handset enabling advanced access to internet-based services with computer-like functions
Subscriptions (Total)[3]	*gensub*	Total unique users who have subscribed to mobile services (subscribers differ from connections such that a unique user can have multiple connections) at the end of the period
Subscriptions (2G)[3]	*gensub2*	Total unique users who have subscribed to 2G mobile services (subscribers differ from connections such that a unique user can have multiple connections) at the end of the period
Subscriptions (3G + 4G)[3]	*gensub34*	Total unique users who have subscribed to 3G and 4G mobile services (subscribers differ from connections such that a unique user can have multiple connections) at the end of the period
Subscription % (Total)[3]	*gensubper*	Unique mobile internet subscribers expressed as a percentage of total unique subscribers
Subscription % (2G)[3]	*gensubper2*	Unique 2G mobile internet subscribers expressed as a percentage of total unique subscribers
Subscription % (3G + 4G)[3]	*gensubper34*	Unique 3G and 4G mobile internet subscribers expressed as a percentage of total unique subscribers

Sources - 1: World Bank (2014); 2: Conference Board (2015); 3: GSM Association (2015); 4: Own Calculations

10.3 Appendix C: Descriptive Statistics

Table 10: Descriptive Statistics - Low-Income Countries

Variable	Name	N	Mean	SD	Min	Max
GDP (in billion USD)	398	43	182	0.142	1600	
GDP growth (%)	398	5.18	4.25	-36.05	21.02	
GDP per capita (USD)	398	577.97	264.12	144.90	1235.45	
Capital Services (USD)	216	460,581	1,433,033	9595	8,707,847	
Employment (in thousands)	224	32,929	87,108	2150	499,299	
Secondary Enrollment (%)	215	43.54	19.63	11.14	105.17	
Tertiary Enrollment (%)	210	9.86	8.35	0.51	47.64	
Smartphone Adoption (%)	400	5.61	6.14	0.12	28.86	
Smartphone Connections	400	1,982,581	9,448,986	121	149,000,000	
Subscription % (Total)	250	28.24	17.17	1.01	95.35	
Subscription % (2G)	250	20.74	14.05	0.25	76.3	
Subscription % (3G + 4G)	211	9.11	8.52	0.01	37.93	
Subscribers (Total)	250	7,083,643	27,000,000	9560	279,000,000	
Subscribers (2G)	250	5,528,549	21,800,000	3734	212,000,000	
Subscribers (3G + 4G)	211	1,842,528	6,099,058	417	66,800,000	

Table 11: Descriptive Statistics - Middle-Income Countries

Variable	Name	N	Mean	SD	Min	Max
GDP (in billion USD)	675	145	438	0.238	5270	
GDP growth (%)	682	3.69	6.42	-62.08	104.49	
GDP per capita (USD)	675	4617.72	2922.99	509.22	15,592.17	
Capital Services (USD)	392	1,622,751	4,966,696	479	42,300,000	
Employment (in thousands)	416	28,968	107,542	67.7	789,614	
Secondary Enrollment (%)	438	85.84	14.22	25.51	110.88	
Tertiary Enrollment (%)	358	41.22	22.13	1.33	117.89	
Smartphone Adoption (%)	695	10.4	10.2	0.05	58.9	
Smartphone Connections	695	5,425,708	36,700,000	45	760,000,000	
Subscription % (Total)	431	43.0	17.8	3.5	84.6	
Subscription % (2G)	431	25.4	13.3	3.3	65.6	
Subscription % (3G + 4G)	382	19.9	15.6	0.02	70.0	
Subscribers (Total)	431	10,300,000	46,900,000	2427	564,000,000	
Subscribers (2G)	431	5,082,128	22,700,000	2427	234,000,000	
Subscribers (3G + 4G)	382	5,937,503	28,900,000	42	396,000,000	

Table 12: Descriptive Statistics - High-Income Countries

Variable	Name	N	Mean	SD	Min	Max
GDP (in billion USD)	382	810	2130	0.994	14,800	
GDP growth (%)	382	1.56	4.52	-15.26	27.50	
GDP per capita (USD)	382	34,538.14	19,896.37	10,091.01	158,602.5	
Capital Services (USD)	320	2,862,031	6,773,258	5346	41,100,000	
Employment (in thousands)	328	11,985	24,806	125	148,600	
Secondary Enrollment (%)	274	104.21	12.35	74.25	165.58	
Tertiary Enrollment (%)	262	61.15	22.53	9.99	116.62	
Smartphone Adoption (%)	407	27.0	20.4	0.46	82.0	
Smartphone Connections	407	6,991,464	20,800,000	644	237,000,000	
Subscription % (Total)	254	64.1	13.3	29.0	89.9	
Subscription % (2G)	251	19.3	12.3	0.3	60.3	
Subscription % (3G + 4G)	248	46.1	18.6	0.66	85.9	
Subscribers (Total)	254	12,100,000	26,900,000	4094	185,000,000	
Subscribers (2G)	251	1,694,651	3,187,090	1832	20,900,000	
Subscribers (3G + 4G)	248	9,780,824	24,800,000	431	170,000,000	

Note: The following descriptive statistics do not include statistics for countries where income group classification was missing and/or not defined (i.e. those where GNI per capita data was missing and thus an income group could not be defined).