The Bass Diffusion Model for Communication Technology Globally and the Economic Factors that Influence it.

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Declaration

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Abstract

Globally over the period 1995 to 2015 there has been an increase in the everyday use of mobile phones and the associated technologies that come with it, but this has led to a digital divide in skill and access levels to these technologies between developed and developing countries. This paper looks to expand on previous research as to the cause and pattern of the adoption rates for mobile users which is used to provide people with access to cellular technologies such as mobile voice communications, sms and internet services. A view of the adoption rate of internet usage will also be analysed in order to have a secondary technology to compare against. It was found that the percentage of the total population that is older than 14 increases the rate of adoption and generational changes in the underlying technology led to a decrease in adoption rates. It was also found that while the wealth of a country is useful for predicting the initial level of adoption rates, it was a poor predictor with regards to year on year changes in adoption rates.

Glossary (Ericsson, 2017)

3G - Third Generation, the name of a global wireless communication standard.

4G - Fourth Generation, the name of a global wireless communication standard.

ARPU - Average Revenue Per User (Subscriber) **-** a measure used mostly by consumer communications and networking companies, defined as the total revenue divided by the total number of subscribers on the network.

CDMA - Code Division Multiple Access – a channel access method used by various radio communication technologies.

CRM – Customer Relationship Management, a field involving the segmentation and subsequent management of the segments in order to increase customer satisfaction and loyalty to the brand.

FED – Fixed Effects Model, a model which explores the relationship between the predictor and outcome variables within an entity. Use fixed Effects Models whenever you are only interested in analysing the impact of variables that vary over time.

ICT – Information and Communications Technology, a term which includes any communication device or application, including: radio, television, cellular phones, computer and network hardware and software, etc. as well as the various services and applications associated with device or application.

Mobile Penetration – The number of cellular subscriptions per 100 people of a given country.

MSISDN - Mobile Station International Subscriber Directory Number, the distinct cellular number per mobile subscriber’s sim card.

OPEX - Operational Expenditure, the cost companies pay to run their primary business operations.

OLS – Ordinary Least Squares create a straight line that minimizes the sum of the squares of the errors generated by the results of the associated equations, such as the squared residuals resulting from differences in the observed value and the value anticipated based on the model.

Post-paid Subscriber – A subscriber who is on a contract with a network and pays an accrued bill for services and goods consumed for that month.

Prepaid Subscriber – A subscriber who pays for goods and services before they are consumed.

Contents

Introduction

From the mid-1980s to 2018 there has been a growing dependence on mobile phone usage by the general population as a source of communication, access to information and for entertainment. The technology changes driving this movement towards an ever increasingly connected world are the improvements in mobile communication technology, and the ability to access the internet. These global technologies gives researchers the ability to study technology adoption on a larger scale than previously, especially in differing economies. This along with multi-generational improvements in the technology, is broadening the field of study when it comes to technology adoption. A generalised understanding of this technology adoption rate could prove instrumental in providing governments, educational programmes and the general business community the ability to understand, predict and react to future technology changes such as artificial intelligence, quantum computing or any other technology that is developed in the near future.

Telecommunications have been in existence for more than a century with the market being dominated by fixed line monopoly companies - until the introduction of the commercially sold mobile phone in the 1980s (Noam 2010, p.5). The telecommunications sector is evolving at a rapid pace with a movement away from the traditional voice phone calls on fixed and mobile cellular phones towards a more data driven consumer as a result of an increase in the use of smartphones (Mckinsey 2016). Previous studies have shown that there has been a growth in the telecommunications sector (Cleeve & Yiheyis 2014), but Ngwenyama and Morawczynski (2009) explain that there are those that believe there is not a clear large positive impact on economic growth for developing countries. This movement towards a data driven communication sector is increasing the scale and speed of globalisation and integration of developing countries into the global economy (Mckinsey 2016). Since 2003 there has been accelerated growth in mobile subscription penetration rates according to data provided by World Bank (2017) in developing counties showing an ever increasing market size for mobile telecommunications. While adoption rates may be converging globally the level of usage and skill of the technology for those classified as already adopted may be at different levels, which is leading to a digital divide between populations (Chen 2014). The structure of the telecommunications sector has also changed over time, with the increasing size and penetration of the sector leading to a more fragmented market as new entrants enter the market in an attempt to gain a portion of the profits (Harno 2010).

This research looks to expand on previous research as to the cause and pattern of adoption rates for mobile and internet users in developed and developing countries using the Bass Diffusion Model as developed by Bass (1969). The Bass Diffusion Model is a concept whereby a new product involving a new technology, has its life cycle broken up into the different stages at which the uptake of the product occurs at different speeds dependent on the stage of the cycle (Bass 1969). The Bass Diffusion Model breaks up the groups of customers who use the new technology by the stage of the lifecycle when they adopt the technology (Bass 1969). Using these concepts, the rate of adoption of new products and technologies can be compared against a baseline. For new variables to be added to the model they would need to improve its accuracy not only just for the one product or technology being analysed, but for future products and technologies as well. The paper will further explore the economic and demographical factors which influence the rate of adoption for new products and technologies, and if generational changes of the same product or technology would impact the rate of adoption. This research builds off the work of Bass and Norton (1987) who added the element of multi-generational influences to the rate of diffusion. It also draws upon work by Jiang and Jain (2012) who added a further level of understanding to the adopters that join at each generation i.e. switchers and leapfroggers, which applies to the ICT sector that has seen four generations of the underlying technology with the fifth generation being developed at the time of writing this paper. Also not forgetting the work of Gelper and Stremersch (2014) who used Bayesian Lasso Regression to test the macro-economic and demographical factors that may impact the change in adoption rates.

The data collection approach used was to take a holistic view of the data with the researcher using aggregated figures provided from the mobile operator's financial statements, a country's regulators website or from international data sources such as the World Bank. The scope of this paper will therefore not include a Mobile Station International Subscriber Directory Number (MSISDN) level of analysis. This has the advantage of no legal obstacles to overcome, and allows for greater data availability. A sample of countries was used instead of every country due to certain countries not having the necessary data available over the period being examined, and the penetration rates across those countries was averaged dependent on which group was being modelled i.e. developed or developing countries. Mendenhall *et al.* (2008, p.421) explain that an experimenter can take the average of many samples in order to obtain a more precise estimate of the average of that sample. Using this, we can understand that the analysis can be accurate by looking at a group of countries averages and not needing to model the penetration by analysing every country's individual past adoption behaviour.

To summarize, the purpose of this paper will therefore be on testing the Bass Diffusion Model as a tool of measuring the adoption of new products and technologies, whether the model is still relevant in a more connected world and if the macro-economic and demographic factors suggested by Jiang and Jain (2012) and, Gelper and Stremersch (2014) can be applied to ICT services adoption rates. Other sub topics that will be viewed are the first and second digital divide, and the characteristics of consumers of telecom products. This paper follows the following structure: a literature review consisting of subsections being a brief history of the telecommunications sector, background on the digital divide, the characteristics of consumers of telecom products in developing countries, the Bass Diffusion Model and finally telecommunication services relationship with a nation's economy. The literature review is followed by the research methodology, empirical results from the collected data and the conclusion to this paper.

1. A Brief History of the Telecommunications Sector, the Digital Divide and Characteristics of Mobile Subscribers

1.1.1. Telecommunications Background

The telecommunications industry emerged in the 20th century, initially with fixed line telecoms followed by the rise of mobile phones from the 1980s (Noam 2010, p.5) to the current era of smartphones and high data consumption (Mckinsey 2016). Koenig (1987, p.586) explained how the type of data that is exchanged would change over time as technologies improve, for example from denser low information data to less dense data with larger bundles of information. This assessment has proven true as mobile technology has evolved over time and there have currently been 4 launched generations with the 5th generation being expected to launch between the years 2018 and 2020. The 1st generation phones had analogue voice calls with no internet capabilities, with the introduction of 2nd generation capable phones consumers were able to access the internet from their phones albeit at speeds less than 0.5 Mbps (simple data) and send text in the form of short message services (SMS). The 3rd generation services brought in the era of smartphones and applications for mobile devices, with internet speeds increasing to roughly 63mbps. While the 4th generation services did not have any new unique features, they greatly improved on the services provided by 3G, internet speeds increased to 300 Mbps and had a higher call quality (Qualcomm 2014).

While mobile phone technology changed, so too did mobile phone adoption rates. With mobile phone penetration growing at a rapid rate, fixed line penetration remained very low in poorer, developing countries (World Bank 2017) which meant that the need for fixed line infrastructure may never grow to support high levels of penetration in those developing countries. This is important to note as it shows that not all technologies or products reach levels of full penetration in a market, but current research suggests that mobile phone penetration may be able to reach full or near full penetration even in developing countries. A study by Cleeve and Yiheyis (2014, p.547) showed that in 1995 African countries without a mobile network were recorded at 52%, but by the year 2000 this number was down to 11%. By 2006 all African countries had some form of a mobile network. Since the early 2000s the number of people using mobile phones per 100 people in developing countries has grown exponentially over a 10-year period (World Bank 2017).

Mobile penetration is calculated using the number of mobile subscriptions in a country divided by the country's population, due to dual sim card phones or multiple phones per person it may lead to mobile penetration being greater than 100%. Internet users per 100 (internet penetration) will always be below or equal to 100% due to the measurement showing how many people use the internet making double counting not possible. Ericsson (2017, p.7) predicts that there were 7.5 billion mobile subscriptions globally in 2016, and that by 2022 that number will rise to 9 billion of which 6.2 billion will be unique mobile subscribers. They also believe that 5G connections will be the leading form of technology for mobile subscribers by 2022, replacing previous technologies such as Edge and WCDMA - "[t]he main barriers to internet access will be illiteracy, affordability and perceived relevance of digital services – not availability of network technology" (Ericsson 2017, p.21).

With broader adoption and usage of a technology comes more attention from governments and regulatory bodies, this held true for mobile technology. With the belief that the telecommunications market was too concentrated, after the mid-1980s there were regulatory changes put in place by governments globally in an attempt to move the telecommunications sector from a monopoly market to a more competitive market (Herrera-Gonzalez & Castejon-Martin 2009, p.664). It can though be difficult for governments to correctly predict technological changes in advance, therefore governments and other regulatory bodies need to evolve their policies in order to keep up and avoid negatively impacting the growth of a sector because of outdated decisions on policy. This can be argued for the telecommunications sector, Noam (2010, p.5) highlights four reasons why governments need to revisit the competitive regulations of the 1980s and 1990s - namely "instability, investment requirements, changing economies of scale and migration of mass media to telecommunication networks".

The telecommunications sector has therefore not only evolved in terms of the service technologies, but also in its market structure with increased competition and the dissolving of monopolies that were in place before mobile telecommunications technology were commercialised. The use of mobile phones has significantly exceeded fixed line subscriptions in developing markets and is set to move away from traditional voice usage to a data driven environment. Regulations have evolved over time as well, but there is still large emphasis on promoting competition in the sector. With the changes that have transpired from the mid-1980s to 2016, it is evident that the needs of the subscriber depends on which environment they are in, the technology they are currently using and the different options available in the market.

1.1.2. First-Level Digital Divide and Second-Level Digital Divide

While the previous section explained that access to mobile telecommunication technology is increasing, it needs to be understood that while any two adopters may have access to the technology they may well have varying levels of skill and usage of the technology. This means that while there is a gap between those that have access and those that do not referred to as a digital divide, there is a secondary digital divide. This section examines those divisions.

Cruz-Jesus *et al.* (2012, p.279) describes the definition of the digital divide from the OECD as "the term digital divide refers to the gap between individuals, households, businesses and geographic areas at different socio-economic levels with regard both to their opportunities to access ICT and to their use of the Internet for a wide variety of activities". This was backed up by Chen (2014) who demonstrated that in the global economy there has become a digital divide between those that have access to ICT services and those that do not. Other papers have attempted to understand the causes of this divide and differing rates of adoption. Schneir & Xiong (2013) showed that the adoption rates of internet access for rural and urban areas have been at different rates with urban adoption growing faster than in rural areas, as well as the internet speeds in urban areas being faster than that in rural areas. Zhang (2013, p.520) explains that there is not only a digital divide between urban and rural areas, but also between developed and developing countries with developed countries adopting the technology faster than their developing peers. Zhang (2013, p.525) went on to show that there is a negative correlation between internet adoption and inequality in a country, while there is a positive relationship between internet access and GDP per capita. This agrees with the idea that a lack of internet access has been suggested to show a decrease in income growth and an increase in unemployment (Whitacre *et al.* 2014, p.1012). However, the research on the linkages of broadband access and economic improvements for areas has been limited (Whitacre *et al.* 2014, p.1012). This means that researchers have been cautious when claiming causality between access to the internet and improvement in economic factors for an area. A study by Cruz-Jesus *et al.* (2012, p.278) looked at the digital divide within the European Union and suggests that it may be due to economic and integration factors. Cruz-Jesus *et al.* (2012) also suggests that the measurement of the digital divide needs to be expanded from those that have and have not to a more detailed approach including reasons for the divide and the divide with regards to different usage of the internet. The term "Second-Level Digital Divide" will be the name used to explain this gap, taken from Chen (2014), it will also be the term when referring to the difference between individuals who have greater online skills and can find information easily as opposed to the more basic user. The Second-Level Digital Divide is important because it shows the inclusion of users into the digital economy as well as their digital productivity (Chen 2014).

While the previous section looked at the possible differences between people who have access and those that do not and, introduced the concept of the Second-Level Digital Divide, this section reviews previous findings that can help to explain the factors that led to the Second-Level Digital Divide. Creative activities and use of the internet have been shown to differ between people who had different parental schooling, as well as online sharing behaviour differing by gender (Chen 2014, p.436). van Deursen and van Dijk (2011) looked at two studies and found that while the level of operational and formal internet skills appeared quite high, the level of information and strategic internet skills is questionable. van Deursen and van Dijk (2011, p.511) also found that education was an important factor for the participants across all skill levels with regards to internet usage, and that age as a factor only impacted operational and formal skills. Tests on a large population sample still seem to be lacking (van Deursen & van Dijk 2011). Brandtzaeg *et al.* (2011, p.124) split users into 5 different clusters from Norway, Sweden, Austria, the UK, and Spain looking at internet usage, with users classified as Non-Users, Sporadic Users, Instrumental Users, Entertainment Users and Advanced Users. Of these users 42% were non-users and only 12% were advanced users. The first digital divide can also contribute to the second digital divide as consumers who adopted the technology earlier have had a longer period of time to upskill and practise with it. Because of these two findings, the causes of the second digital divide can be both socially constructed in terms of gender and situational (rural vs urban populations, or rich vs poor consumers).

There are therefore various factors that contribute to not only the gap between consumers that have access and those that do not, but they also contribute to the consumption and skill level for said technology within the group of consumers that are already classified as adopters. While this paper will not model the Second-Level Digital Divide it is important to understand the difference between the two divides in order for complete comprehension of adoption rates.

1.1.3. Varying Characteristics of Mobile Subscribers

As with any product sold on a large scale, consumers of the product can exhibit different traits with regards to price elasticities and usage patterns, which is the case with telecommunication products and services. Findings showed that tariffs and usage fees negatively impacted ICT technical efficiency expansion (Ngwenyama & Morawczynski 2009). Various studies of mobile demand elasticities have shown moderate price elasticities. Earlier studies, those which occurred during 1999 to 2008, on phone call demand elasticities showed elasticities of between 0 and -0.9. The challenge with some telecom studies is the difficulty of showing whether fixed and mobile subscriptions are complements or substitutes to each other. The rest of this section will look at studies that show the varying price elasticities and characteristics of mobile subscribers. This will help understand how improvements in economic conditions can drive higher adoption rates due to disposable income increasing for the population of the various countries being studied.

Haucap *et al.* (2011) paper looking at demand elasticities in Turkey found that there was a rising level of purchases of prepaid sim cards compared to post-paid sim cards. This could be due to the high interconnect prices between networks. Own price elasticity was found to be lower than aggregate market elasticity. Post-paid sim cards generally have lower elasticity levels as compared with prepaid sim cards, which could be caused by the process of proving credit worthiness for a contract eliminating the poorer subscribers who do not have stable financial backgrounds and are more inclined to look for better prices (Haucap *et al*. 2011). Another reason that post-paid subscribers may be less elastic than pre-paid subscribers could be due to the post-paid subscriptions having company contracts that are used for business, and therefore the subscriber is not able to delay a business call regardless of the price paid to utilise the service. Haucap *et al.* (2011) found that in Turkey there appears to be no significant difference between the elasticity of demand measured for the short-run and the elasticity of demand for the long-run for prepaid subscribers.

Jacobin and Klein (2013) performed an online survey in an attempt to ascertain consumers most important needs in a bundle offered to them by an operator consisting of telecommunications services such as voice, sms and data. It was observed that the basic fee to obtain the bundle was the most important factor for the consumer. Gryzbowski and Pereira (2011, p.24) show that the consumer perceives switching networks to be costly, be it due to direct costs of contract termination and buying a new sim card and the indirect cost of the time taken to inform friends and family of the subscribers' new number being the highest indirect cost. They went on to further explain that subscribers as a whole are price elastic when it comes to purchasing telecommunications services, but that the level of price elasticity varies by network operators and their consumers. When the research was completed on a set of subscribers in Portugal it showed that the averages for the three networks included in the study were -1.65, -2.10 and -2.33 thus proving that consumers are price sensitive (elastic). The cross price elasticity of demand with operator one opposed to the other two operators was found to be 1.29 and 1.24 indicating that the consumer viewed the services of the operators as substitutes and a 1% increase in operator one's prices would lead to a 1.29% and 1.24% increases in its competitors' subscriber base.

Ngwenyama and Morawczynski (2009) explained that in developing countries the consumers were believed to be very price sensitive to ICT services. This would be expected due to poorer developing country populations having lower incomes when compared to developed countries. An older study by Dewenter and Haucap (2004) looked at the elasticity of demand for mobile phone users in Austria for the year 2004. Their findings demonstrated that with statistical significance there were negative price elasticities of demand varying from -0.19 to -3.56 depending on the sample they were using.

Ramachander (2016) performed a study on mobile price elasticities in Asia, their findings are discussed further below. It was mentioned that regulations that encourage competition have driven down the price it costs to use a mobile phone, and pre-paid sim cards have helped lower income users to start using mobile phones as the cost to entry is cheaper than that of post-paid or contracts. Ramachander (2016) goes on further to explain that the lack of penetration for fixed line subscriptions in some developing countries has actually helped with the adoption of mobile subscriptions, but a difficulty in developing markets when formulating the pricing for telecommunication services is that the general population are low income earners and therefore, finding a price that they will be able to afford along with the price making economic sense to the operator needs to be calculated. Ramachander (2016) used a survey on low income households in the countries of Bangladesh, India, Pakistan, Philippines, Sri Lanka and Thailand with nearly 10 000 respondents. Some of the findings were:

- Those who have had mobile phones for longer are less price sensitive than new adopters of mobile phones.
- Subscribers who would top up their pre-paid account with higher bundle volumes were less price sensitive than those that topped up with smaller bundle volumes.
- Mobile users who have multiple sim cards on one device are shown to be very price sensitive due to the ability to substitute the more expensive operators' service for the cheaper operators' service almost instantaneously.
- Subscriber loyalty decreases the subscribers' price sensitivity to change in usage with regard to the operators change in prices for their service offerings.
- Subscribers who are more active with their mobile phone are shown to be more price sensitive in terms of their mobile phone usage.
- Demographic variables were not very important in price sensitivity, but were an important factor in terms of the likelihood of mobile phone ownership.

The final study that was reviewed on price sensitivity in the mobile telecommunications sector for voice was by Stork (2016). The study found that competition in the mobile sector has driven down the cost of mobile services, which is consistent with the findings of Ramachander (2016). Some of the barriers to use for mobile phone consumers include no access to mobile reception, the high costs of handsets, high minimum recharge vouchers and a lack of access to electricity to keep the mobile phone charged and working (Stork 2016). Those unable to pass the mentioned barriers will need to find other avenues of communication, for example using a public phone. Lastly, Stork (2016) shows that when consumers have high income increases, they will move the consumer from pay phones to higher mobile phone usage as they are now able to afford the ownership costs of a mobile phone. A final factor that plays a role in the movement of a subscriber from one network to another due to price changes is the accessibility of information on the prices of other operator. Often in markets the information to the consumer is incomplete therefore leaving the market out of equilibrium and raising the cost for a subscriber to use and alternative service (Black *et al*. 2010, p.25).

Since the 1980s the telecommunications sector has seen a change in both technology and in market structure as regulators have pushed for a more competitive market. While these more competitive markets and the ability for consumers to buy older versions of the technology have brought down prices, there is still a gap between access, usage levels and the skills involved with telecommunications services. These gaps have been categorised into two levels being the First-Level Digital Divide and the Second-Level Digital Divide. First-Level Digital Divide is the divide between those that have access and those that do not while the Second-Level Digital Divide is the gap with those that have access, but have different usage and skill levels. Finally this section showed how consumer's income levels can lead to increased or decreased rates of adoption due to their being evidence of negative price elasticities to telecommunication products. This helps explain why richer developed countries have higher mobile and internet penetration when compared to their poorer developing peers.

1.2. The Bass Diffusion Model

The Bass Diffusion Model is a theory that is used to predict and understand the rate of adoption for a new product or technology (Bass 1969). It looked at the adoption of a new technology by breaking up the cycle into parts with differing speeds of adoption as well as breaking up the consumers into differing characteristic groupings using the stage of the cycle that they adopt the technology. This model has been used in numerous studies to forecast the growth of different fields within the telecommunications and other technological sectors. A few of the studies include Turk and Trkman (2012) who used the Bass Diffusion Model to predict broadband penetration for European OECD countries, Orbach and Fruchter (2011) who used the Bass Diffusion Model in its forecasting of technology adoption, Meade and Islam (2015) who used the Bass Diffusion Model to forecast adoption in the ICT sector, Frank (2004) who used the model to predict mobile penetration rates in Finland and, Wu and Chu (2010) who used the model to study mobile penetration levels in Taiwan.

The model shows that the adoption of the new technology follows an S shaped curve as it starts off slowly and then speeds up followed by an eventual levelling off (Harno 2010). These three periods of adoption make a full cycle of adoption. The product cycle is broken up into three stages namely the new-product stage, the maturing-product stage and the standardized-product stage (Appleyard *et al*. 2010). The consumers are characterised by when they join, which is used by Bass (1969) to group consumers into five chronological groups; innovators, early adopters, early majority, late majority and laggards, based on when in the cycle of the S curve they adopted the technology. For the purpose of this study the 5 groups were joined into three to fit into the 3 stages of the S curve. This was done by grouping the early adopters, early majority and late majority into one group being "adopters" which are chronologically between the innovators and the laggards.

Meade and Islam (2015) performed a study on forecasting in the telecommunications and ICT sector. The term ICT is both for hardware and software and includes telecommunications. ICT can be looked at in three subsections being mobile telephony, internet usage and other ICT products (Meade & Islam 2015, p.1106). Diffusion modelling and forecasting, time series forecasting, and technological forecasting are the three main forecasting approaches used in this study. Internet usage revenues is believed to have passed voice and sms revenues in developed countries. Meade and Islam (2015) defines the Diffusion Model as:

> "The process by which an innovation is adopted by a population. Relevant examples of innovations are, historically, fixed line telephony, or, currently, mobile telephony. The diffusion process is characterised initially by the introduction of the innovation, followed by a slow growth in adoption as awareness increases. The growth accelerates to a point where adoptions per period peak, then adoptions decelerate as the population becomes saturated with the innovation".

In the first stage, the product/technology is produced and sold in the domestic market, and the producer generally has a monopoly due to patents (Appleyard *et al.* 2010, p.177). It is believed that if firms in one country create a new kind of technology there will be a lag for that technology to be exported and implemented by other countries (Appleyard *et al.* 2010, p.177). There is also an expected lag after the other countries start using and selling to the consumers whereby demand takes time to increase due to lack of information about the new product, inertia to older similar products, sunk costs in inferior products, etc. (Appleyard *et al.* 2010, p.180). With a lag in exporting, there will be limited access to this technology in other countries which in turn will mean that the product will be expensive with a slow initial adoption rate. At this stage the product does not have older models where the previous technology of that product can be sold at a discount price due to the new to the market product. This means that if a consumer's domestic market is technologically advanced their adoption of a new technology should be faster than that of a consumer in a country with limited technological innovation.

The second stage is where the product/technology demand increases (Appleyard *et al.* 2010, p.177). The producer grows and starts to standardise the good, and develops economies of scale. As demand grows further into other markets the producer will start exporting the good (Appleyard *et al.* 2010, p.177). The price of the product starts to drop with efficiency in production taking place, and older models can be sold at a discounted price.

The third stage is where the good is in the final process of being fully adopted and the producer has had to open up operations in foreign markets to produce their good due to cheaper costs (Appleyard *et al.* 2010, p.178). The country of the original producer imports the good as well as exporting it due to the lower costs of producing it abroad (Appleyard *et al.* 2010, p.178). In the third stage the penetration of the good even in the lagged countries will begin to slow down as there is less room for organic growth with most of the population already having access to the good.

With organic growth slowing and prices decreasing, new streams of revenue need to be looked at in order to guarantee long run returns in a business climate that is seeing diminishing returns, such as in the telecommunications sector with voice revenue (Harno 2010). In the study by Harno (2010) the base case model is examined with consumer spending and consumption as a reaction to technological enhancements considered. The economies of the business user are examined after the technological enhancements. In terms of usage it is stated that the elder business population users have a higher opportunity cost with delays in line speed when compared with younger people. It is shown that subscribers who have faster network access use significantly higher amounts of data and this translates to them becoming higher ARPU subscribers. An indication that investment into improving the service infrastructure does have benefits. Harno (2010) also shows that in order to keep profits up in the future operators are going to need to find ways to bring down their operation expenditure (OPEX) costs.

Due to the telecommunications market being fragmented, infrastructure does not evolve optimally as each operator is just looking to obtain their own revenue share (Harno 2010). The investment in improving the current technology for example moving from 3G to 4G will generally take place in wealthier areas as the population in those areas will be able to afford it. This is a natural segmentation as the initial adopters will be wealthier on average. Digitization has increased globalisation in the 21st century and has lowered costs for smaller business to become global players and therefore lowered the barriers to entry for global business (Mckinsey 2016), which has helped speed up the adoption phase in the product cycle especially for mobile phones.

Frank (2004) designed a model to study Finland's mobile telephone subscriptions per 100 people (mobile penetration). It showed that an economy with a faster growing GDP will have a higher rate of diffusion. When looking at mobile penetration, 100% penetration is not the upper limit for total mobile subscribers, only if unique subscribers could be counted then 100% penetration in terms of subscribers and not sim cards would this then be something that could be calculated. The difficulty with knowing unique subscribers is due to the fact that people use multiple sim cards, use business sim’s that are not in their names and buy sim’s for friends and family that will not be in the friends or family members name. For those reasons the number of total mobile subscriptions per capita is preferred and often leads to penetration of over 100% (Meade & Islam 2015). This makes it difficult to be able to accurately measure the potential subscriber base of a country. Meade and Islam’s (2015) study reviewed previous studies. The first reviewed study using data from 90 cities in the USA in 1998, found that an additional fixed line had a higher price elasticity than the initial line. This is useful because if you apply the same principle to mobile phones you can segment new numbers on the network even if one subscriber has more than one number. It was also found that there has been a slowdown in fixed line subscriptions due to the substitution effect with mobile subscriptions. The next reviewed paper Wu and Chu (2010) showed that by using Taiwanese data, the initial adoption stage (take-off stage) reaches its peak between 10-20%. Case dependency does impact the model used. Donganoglu and Grzybowski (2007) found that in

Germany the demand for mobile subscriptions depends on lagged cumulative subscribers and service prices. It can be shown that the accuracy of forecasting decreases if the forecast is longer than a four-year time frame. Islam and Meade (2015, p.1113) explained that

> "[t]hey find that income/head, urbanisation and internet penetration have a positive impact on diffusion across all generations, however, although the diffusion of the first generation (analogue) stimulated the diffusion of the second generation (digital), the diffusion of the second generation did not affect the diffusion of the third generation. Countries with a higher economic globalisation index (e.g. a greater openness to trade) are associated with higher rates of diffusion."

This gives an indication that improving the product can speed up the diffusion process and the degree of the innovation decides the degree that it accelerates the diffusion process. Meade and Islam (2015) explained that there was a general pattern in findings that state that the level of prices and competition are important factors in the speed of the diffusion process. This would agree with the ARPU decreasing as the penetration levels increase due to the technology becoming more affordable and allowing lower income earners with lower potential spending on the services to be able to start using the product. A study by Lee *et al.* (2010) looked at patents in the United States and their spill over to the Bass Diffusion Model. The research for the study was limited to Code Division Multiple Access (CDMA) of which Qualcomm owns the patents on CDMA technology since the 1990s. In the study they break up consumers in the Bass Diffusion Model into innovators and imitators. Innovators adopt the new product as a result of external influence. Imitators adopt the new product due to word of mouth. The mobile industry has a relatively short time period from a patent being filed and the technology being commercialised (Lee *et al.* 2010). With technology there is a difficulty in accurately estimating the market potential in the early stages of the Bass Model. The mobile market in terms of its technology is already in the mature stage of the Bass Diffusion Model. The diffusion of mobile phones can be accelerated by new CDMA technologies. The diffusion of technology can help with the forecasting of the diffusion of a new technological product.

Chung (2011) looked at the impact of internet reviews, positive and negative, on the diffusion of a product. Chung (2011) proposed that positive online feedback will accelerate the diffusion process and negative feedback will negatively impact the speed of the diffusion process. Online activity in terms of the mentioning of a product, unless very negative, will speed up the diffusion process of the product. The volume of online mentions of a product are more significant in predicting an accelerated increase in terms of diffusion of the product than whether the comments were positive or negative (Chung 2011, p.1188).

Zhang (2013) discuss the two different diffusion curves that show different adoption rates over time. The two curves are the Diffusion of Innovations Theory (DIT) and the Technology Acceptance Model (TAM), which help to explain the behaviours that lead to adoption of an innovation. The DIT, first proposed in 1962, focuses on the five attributes of innovations: relative advantage, compatibility, complexity, trial ability, and observability. The TAM curve focuses on the psychological determinants of the technology adoption behaviours. The DIT and TAM both show unique insights for the Internet diffusion adoption rate. However, they fail to show one important fact, Internet devices (such as desktops, laptops, and tablets), and access services (such as the dial-up and broadband cable) that are sold. From this view, the Internet diffusion rate is also the behaviour of internet consumption. When internet adoption is categorised as a form of consumption behaviour, Consumption Theory should not be excluded from the theoretical analysis. However, if the internet usage is treated similarly to the goods which have no technological attributes in terms of usage, then the uniqueness of internet consumption will be neglected. This indicates that the strengths and weaknesses of the DIT, the TAM and Consumption Theory show a great potential of theoretical integration.

The final paper on diffusion modelling that was reviewed for this paper (Orbach & Fruchter 2011) looked at technology diffusion forecasting by using investment in research and development as well as past technology progression rates. Adoption rates of electric cars were the focus of this study. Generally, after a technological product has been in the market for a while there will be improvements in the product or services involving the technology. These technological changes to the product can help lead to rapid growth and a decline in prices of the product or service. An increase in marketing as well as word of mouth on social media can change the rate of diffusion in the Bass Diffusion Model (Orbach & Fruchter 2011, p.1211). In the product cycle the infant stage can be categorised by more rapid growth of the product and growth in research and development spending on the products technology, but as the product hits the mature stage of the cycle where growth in penetration starts to flatten out the research and development investment spending growth will slow down (Orbach & Fruchter 2011). Customers are forward looking and when they receive information about future products before the products are launched it can speed up the adoption of the product due to the consumer having already decided on buying the product due to previously disclosed information. Predicting the adoption rate and sales growth at the early stages of the diffusion model is believed to be the most challenging part of the product adoption cycle.

From the reviewed studies, there are several assumptions that can be made and used when studying the collected data on mobile penetration levels in order to provide adoption conclusions. Firstly, early adopters are higher spenders and income earners than late adopters. Secondly, the more a product is advertised or communicated about the faster the adoption cycle. Thirdly, consumers in developing countries have higher price elasticities than that of consumers in developed markets. Fourthly, the more technologically advanced the country a consumer lives has an on impact the speed of adoption of technologies. Lastly, when a subscriber gets a second mobile connection they generally are more price sensitive for their second connection. This shows that it is possible to distinguish between subscriber characteristics by simply knowing when in the cycle they adopted the product/technology.

1.3. Telecommunications and the Economy

While the telecommunications sector is making it easier to conduct business and communicate over large distances with services such as the internet, e-mail and social media, there is a debate over the impact that telecommunications growth has on a nation's economy and whether economic growth helps the telecommunications sector grow at a faster rate. Which economic and social metrics to compare when testing the impact that these services have on a countries well-being and vice versa need to be viewed in order to accurately model the relationship. Two common metrics that are used are economic growth and economic development, which explain different measures of advancements for an economy. Economic growth is the increase of national income while economic development is used to describe increases in health care, education, policing, etc. Gross Domestic Product (GDP) and Gross National Product (GNP) are used to measure the levels of economic growth for a country. The challenge with utilising these measures is that they do not take into account factors that have no market value with reduction in crime or low levels of pollution being examples. The informal sector is often not taken accurately into account when calculating GDP due to lack of information on its exact size and scope (Perkins *et al.* 2013, p.26).

There are two different schools of thought in terms of telecommunications impacting growth for developing countries. The first being that it helps growth, the other that it hampers growth and increases the gap between the rich and the poor (Cleeve & Yiheyis 2014, p.549). The first school of thought believes that a growing telecommunications infrastructure has helped developing countries' economies grow. It believes that it reduces the level of asymmetric information and lowers transaction costs for rural agriculture and commodity trade. It also believes that the improved telecommunications infrastructure boosts healthcare treatment, security and various other sectors that can improve the life of people living in low income countries (Cleeve & Yiheyis 2014, p.549). Further research by Datta and Agarwaltz (2004, p.1649) state that the positive link between fixed investment and economic growth has been shown in previous studies, but Ammar and Eling (2015, p.257) note that the lack of infrastructure investment studies makes it difficult to show clear returns for the large capital outlays needed by a state to build the infrastructure. It can be argued that growth in the telecommunications sector of a country increases productivity of firms in said country (Datta & Agarwaltz 2004, p.1650). Increasing technical efficiency in a country will push the production possibilities curve further outwards and lead to economic growth (Black *et al*. 2010, p.22) which will support the idea that increased information and communication technology investment will improve a countries productivity.

Global trade and tourism has drastically increased from 1990 to 2014 (Mckinsey 2016). Ngwenyama and Morawczynski (2009) show that an expansion of ICT infrastructure is helpful to enable cross-border trade and investment. In the 21st century globalisation has led to higher rates of information transfer across borders. The digitization that has increased globalisation in the 21st century has lowered costs for smaller business to become global players and therefore lowered the barriers to entry for global business. Globalisation has both economic and non-economic definitions.

Economic globalisation is the integration of a national economy into the global economy where countries can trade goods and services, technologies and investments (Perkins *et al.* 2013, p.10). Non-economic globalisation involves the migration of people, communication avenues between countries, integration of different cultures and shared political ideologies (Perkins *et al.* 2013, p.10). Mckinsey (2016) believes that the increase in trade and data has increased global GDP by roughly 10%, the value of which was $7.8 trillion in 2014. Traditional media houses are moving away from targeting local markets to global markets. Small and medium sized enterprises (SMEs) now have a strong digital footprint with there being a very strong presence on Facebook (Mckinsey 2016). Trade is an important factor in growing an economy and it is argued that large amounts of ICT investments for developing countries are needed to help integrate them into the global economy (Bankole *et al.* 2014, p.29). African countries often must make a trade-off between investing in things like clean water sources to communities, housing projects, etc. and investing in ICT infrastructure (Bankole *et al.* 2014, p.30). It has been shown that increased access to internet can improve developing countries export performance (Bankole *et al.* 2014, p.32). The model shows that both telecommunications and institutional quality have a positive statistically significant impact on trade in Africa (Bankole *et al.* 2014, p.32).

The second school of thought believes that the rise of telecommunications has negatively impacted low income countries as it widens the gap between the rich and the poor. Rural populations without proper access to internet are being locked out of the information transfer and leaves them at a disadvantage compared to those that do have access to the information (Cleeve & Yiheyis 2014, p.550). In order to produce goods an economy needs capital and labour, and when there are technological improvements the required levels of labour and capital needed to produce the output can decrease (Appleyard *et al.* 2010, p.209). In developing countries this improvement in technology can lead to issues whereby the country is labour abundant and there is a reduced demand for labour (Appleyard *et al.* 2010, p.210). This may be why it was found that increasing mobile phone penetration rates does impact GDP growth positively, but only by very small amounts (Cleeve & Yiheyis 2014, p.557). The opposite was not found for GDP growth impacting mobile penetration (Cleeve & Yiheyis 2014, p.557). Ngwenyama and Morawczynski (2009) states that there are those who are not fully convinced that significant ICT investment for emerging economies is the answer to growth, and that the positive impact of ICT investment on GDP per capita growth only happens after a particular level of ICT development. It is difficult to put a monetary value on the benefits brought to consumers thus GDP may not reflect this accurately (Mckinsey 2016).

Developed countries have stronger data flows than developing countries. Since 2008 there has been a slowdown of traded goods, services and finance which seems to not be due to a cyclical factor, but more towards a structural change. Roughly 12% of the trade of global goods is done via e-commerce (Mckinsey 2016). Business to consumer transactions are increasingly becoming cross border transactions due to e-commerce (Mckinsey 2016). With the increases in data flows between countries and an increase in the access to information, copyright of certain ideas is becoming increasingly difficult to protect. Copyright laws are important to incentivise producers to innovate. Without copyright laws producers could copy someone else's innovation and price them out of the market as their development costs would have been significantly lower (Sanz 2015, p.208). In a dynamic setting the innovation from copyright laws add economic value to a society, however in a static setting it decreases social welfare as the product cannot be reproduced or improved on by another supplier, therefore handing the supplier with the copyright monopolistic rents (Sanz 2015, p.209).

The dynamic setting increase in welfare can offset the static situations losses because of the incentive to innovate that comes from copyright laws (Sanz 2015, p.209). In the digitalized age, the enforcement of copyright right laws are becoming increasingly difficult as file and information sharing make it possible for the product to be distributed without remuneration to the producer of the product with the copyright (Sanz 2015, p.209). Economists argue that the costs of enforcing copyrights could exceed the economic benefits to the producer holding the copyright. There is currently a strong debate about the impact that digital file sharing has on the revenues of the content producers holding the copyright. It is believed that file sharing has decreased revenues for original content providers although some argue this is not the case and that there seems to be no significant impact on the supply of copyrighted content due to file sharing. Doing away with copyright laws there could still be incentives to innovate as the producer would achieve benefits from the first mover advantage (Sanz 2015, p.210). An example of this is if firms in a country create a new kind of technology there will be a lag for that technology to be exported and implemented by other countries. There is also a lag after the other countries start using and selling to the consumers whereby demand takes time to increase due to lack of information about the new product, inertia to older similar products, sunk costs in inferior products, etc. (Appleyard *et al.* 2010, p.210). Therefore, with continued innovation the lag that takes place before lower cost countries can reproduce a similar good should still give the innovator profits from developing the new product or service. A big question in the copyright debate is over the quality of goods being produced under copyright law. The measure of the value of these copyrighted innovations can fall under intellectual capital, which can be a very important asset. Dumay and Rooney (2016) go deeper into the explanation of intellectual capital. Government Business Enterprises (GBEs) will offer a service or a product to the consumers in order to recoup the costs in providing the service or creating the product. The price of the service can be difficult to accurately account for due to a service having intellectual capital as one of its main inputs and the intangibility of the input asset. Intellectual capital was first considered a need for reporting to provide evidence that a business has a competitive advantage and then the definitions, measures and frameworks needed to be formulated. There is wide debate on how to account for intellectual capital due to its intangible nature (Dumay & Rooney 2016, p.1).

All of these factors add to the debate on whether spending money on ICT investment is the best use of public funds. Investing in telecommunications, therefore needs to be assessed in terms of the pros and cons of the investment needed for the country as well as some of the other issues in the economy that need addressing. There are benefits in improving the telecommunications infrastructure of the country, being increased productivity and better access to information, but if this comes as a cost to other areas that need development, such as educational spending where the labour force is unskilled, there could be large increases in unemployment as the economy will be forced to move to a machine intensive state and outsourced labour market. Intellectual property theft due to data sharing across borders that is difficult to police can add to the negative argument on a connected world due to innovator profits decreasing and driving down incentives to innovate.

2. Research Methodology

The Bass Diffusion Model has been used in research to predict and understand the diffusion rate of a new product or technology. The original Bass Diffusion Model by Bass (1969), however does not take into account external variables such as macro-economic and demographical factors, or internal factors such as multiple generational versions of the technology or product, which may influence the speed of adoption at the various stages of the new product or technologies life cycle. Bass and Norton (1987) added the element of multi-generational influences on the rate of diffusion. Jiang and Jain (2012) then added a further level of understanding of the adopters that join at each generation i.e. switchers and leapfroggers, which applies to the ICT sector that has seen four generations of the underlying technology with the fifth generation being developed at the time of writing. As the goal of this paper is to further analyse the causes for the rate of diffusion, the application of the generational variable will need to be taken into account and tested in order to understand whether it plays a role either negatively or positively in the speed of adoption for the ICT services being analysed. If the generational changes in technology are found to have a statistically significant impact on the adoption of ICT services being analysed in this research then the proposed additions to the Bass Diffusion Model by Bass and Norton (1987) and, Jiang and Jain (2012) will be shown to still be correct with modern technologies on a global scale. The second addition that will be reviewed with regards to the Bass Diffusion Model is the various macro-economic and demographical factors that may impact the speed of adoption for ICT services. These economic factors have been previously tested by Gelper and Stremersch (2014). This works uses the same methodology used by Gelper and Stremersch (2014) with regards to using the Bayesian Lasso regression models that will be used to test the macro-economic and demographical factors that may impact the change in adoption. It will though be in combination with a Stepwise Ordinary Least Squared (OLS) regression, using the Akaike Information Criterion (AIC) value in order to choose the best model, over the same period. The mathematical formulas of the Bass Diffusion Model (1969), multigenerational influences on the rate of diffusion by Bass and Norton (1987) and, Jiang and Jain (2012) as well as the macro-economic and demographical factors that may impact the change in adoption by Gelper and Stremersch (2014) will be discussed, followed by the empirical findings on the data collected for this research in the next section.

2.1. Previous Research Models for Bass Diffusion Model and its Subsequent Augmentations

The Bass Diffusion Model was first discussed by Bass (1969) and, the theoretical components and its previous uses were discussed in the literature, but the mathematical components will form the fundamental base that the other augmentations are built off of and will therefore be viewed first. The mathematical models provided below have been taken from work by Bass (1969), Norton and Bass (1987), Jiang and Jain (2012), and Gelper and Stremersch (2014). These models will provide context for both the theoretical reasoning's behind the variables that were selected in the Stepwise OLS and Bayesian Lasso regression models, and the reasoning for using the Bayesian Lasso regression modelling techniques in combination with Stepwise OLS regressions for the data in this research.

2.1.1. The Bass Diffusion Model

Below in equations 1 up to and including 3 is the basic Bass Diffusion Model (Bass 1969, p.217).

$$P(T) = \frac{[f(T)]}{[1-f(T)]}, \quad f(\mathrm{T}) \text{ likelihood of purchase at time T and } F(T) = \int_0^T f(t)dt, \;\; F(0) = 0 \quad (1)$$

$P(T)$, this is the probability of purchase at time T if there had been no prior purchases of the product or technology and m is the population of purchasers.

$$P(T) = p + \frac{q}{m}Y(T), \text{ where p and } \frac{q}{m} \text{ are constants and Y(T) are previous buyers} \quad (2)$$

$$P(T) = p + qF(T) \quad (3)$$

Formula 3 is the Bass Diffusion Model where by F(t) is the installed base fraction, the coefficient p is the coefficient of innovation, external influence or advertising effect and the coefficient q is the coefficient of imitation, internal influence or word-of-mouth effect.

Bass (1969) then provides further calculations for the model in order to predict the total and peak sales of a product, which will be important as this provides businesses with the information needed to understand the product or technologies life cycle. First the total sales $S(T)$ and peak sales at time T is provided in the equations 4 through 28 followed by the time it will take to achieve peak sales in the equations 29 and 30.

$$f(T) = [p + qf(T)][1 - f(T)] \quad (4)$$

$$f(T) = p + (q-p)\,F(T) - q[F(T)]^2 \quad (5)$$

$$F(T) = \int_0^T f(t)\,dt, \quad (6)$$

Since $f(t)$ is the likelihood of purchase at T and m is the total number purchasing during the period for which the density function was constructed,

$$Y(T) = \int_0^T s(t)dt = m\int_0^T f(t)dt = mF(T), \quad (7)$$

is the total number of purchasing in the (0, T) interval.

$$\therefore \text{ Total Sales at } T = S(T) \quad (8)$$

$$S(T) = mf(T) \quad (9)$$

$$S(T) = P(T)[m - Y(T)] \quad (10)$$

$$S(T) = [p + q\int_0^T \frac{S(t)dt}{m}][m - \int_0^T S(t)dt] \quad (11)$$

$$\therefore S(T) = p.m + (q-p)Y(T) - \frac{q}{m[Y(T)]^2} \quad (12)$$

$$S_t = S(T) \quad (13)$$

$$S_t = a + bk(T)Y_{t-1} + ck^2(T)Y^2{}_{t-1} \;, \quad \text{Where } K(T) = Y(T)/Y_{t-1} \quad (14)$$

Parameter Estimation for S_t

$$S_t = a + bY_t{}^{-1} + cY^2{}_{t-1} \quad (15)$$

T = 2, 3, … where S_t = Sales at T and $Y_t = 1 = \int_{t-1}^{T-1} S_t$ = cumulative sales through period T – 1. (16)

- a estimates pm
- b estimates q – p
- c estimates –q/m , -mc = q , a/m = p

$$\text{Then } q - p = -mc - a/m = b \quad (17)$$

$$\text{and } cm^2 + bm + a = 0 \quad (18)$$

$$\text{Or } m = -b \pm \frac{-b \pm \sqrt{b^2 - 4ac}}{2c} \quad (19)$$

- m = km
- q = 1/kq
- p = 1/kp

$$S_0 = 1^{st} \text{ years sales} = a \quad (20)$$

$$S_1 = 2^{nd} \text{ year sales} = a + a.b + a^2c \quad (21)$$

$$S_2 = 3^{rd} \text{ year sales} = a + (S_1)b + S_1{}^2c \quad (22)$$

$$\therefore a^1 = S_0 \quad (23)$$

$$b^1 = Simultaneuos\ equation\ S1\ and\ S2 \quad (24)$$

$$c^1 = Simultaneuos\ equation\ S1\ and\ S2 \quad (25)$$

$$p = \frac{a}{m}\ (innovation\ coefficient) \quad (26)$$

$$q = -mc\ (immitation\ coefficient) \quad (27)$$

The maximum of new products sold is equal to S′. This is the peak sales and is shown in equation 28.

$$S' = \frac{\left(\frac{m}{p(p+q)^2\, e^{-(p+q)T}}\left(\frac{q}{pe^{-(p+q)T}} - 1\right)\right)}{\left(\frac{q}{pe^{(p+q)T}+1}\right)^2} \quad (28)$$

Time to Peak Sales (derivative of S′) is shown in the equations 29 and 30.

$$\mathrm{T} = -\frac{1}{(p+q)LN\left(\frac{p}{q}\right)} \tag{29}$$

$$\mathrm{T} = \frac{1}{(p+q)LN(q/p)} \quad \text{, if local max exists q > p} \tag{30}$$

Using this model the number of sales at a given point in time (equation 12) as well as the number of peak sales (equation 28) and the time to get to the peak sales (equation 30) can be calculated. These equations from Bass (1969) gave researchers a fundamental starting point for calculating and understanding the rate of adoption for new products or technologies. Products and technologies are often improved over time with the different generations of mobile technology being an example of such improvements and can therefore, impact the adoption of the product or technology. These impacts were examined by Norton and Bass (1987) initially, and then by Jiang and Jain (2012) who provided an augmented model of the Bass Diffusion Model that incorporated these generational changes. This addition to the model evolved it further and gave a better overall understanding for the rate of adoption not only for the first generation, but for future generations of the technology or product.

2.1.2. Norton-Bass Diffusion Model

Building off of the original work of Bass (1969), Norton and Bass (1987) augmented the model by adding a generational component to the original Bass Diffusion Model. This allowed for a multi-generational analysis of a new technology or product. The model is known as the Norton-Bass Diffusion Model. This multi-generational model is relevant to this research as mobile technologies have undergone several generations since inception in the 1980s.The Norton-Bass Diffusion Model can be shown with a two generational models initially followed by a multi-generational model. In the simplified first model from Norton and Bass (1987) with only two generations of a product or technology, generation 1 (G1) at time 0 while generation 2 (G2) is at time τ_2, the sales rate of these two generations were represented by two equations:

Generation 1:

$$\mathrm{S_1(t) = m_1F_1(t) - m_1F_1(t)F_2(t - \tau_2)} \tag{31}$$

$$S_1(\mathrm{t}) = m_1F_1(t)[1 - F_2(t - \tau_2)] \tag{32}$$

Generation 2:

$$S_2(t) = m_2F_2(t - \tau_2) + m_1F_1(t)F_2(t - \tau_2) \tag{33}$$

$$S_2(t) = F_2(t - \tau_2) + [m_2 + m_1F_1(t)] \tag{34}$$

In equations 31 and 32, m_1 represents the market potential for generation 1, and m_2 is the market potential unique to generation 2. According to Norton and Bass (1987), all potential adopters of generation 1 are also possible adopters of generation 2. A multi-generational model $F_G(t)$ gives the Norton-Bass Model the following form:

$$FG(t) = 0, \quad if\ t < 0 \tag{35}$$

$$FG(t) = 1 - \frac{e^{-(PG+qG)t}}{\left(\frac{qG}{pG}\right)e^{-(PG+qG)t}+1}, \quad if\ t \geq 0 \tag{36}$$

Where P_G and q_G are the *coefficient of innovation* and *coefficient of imitation*, respectively, for generation G. In this study, $F_G(t)$ was interpreted as representing the diffusion rate of adoption concerning generation G, and $S_G(t)$ as representing the number of units in use for generation G.

While this added the generational aspect of a new product or technology it did not distinguish between consumers who had previously purchased previous generations and consumers who skipped generations of the new product or technology. This aspect of the generational consumer's sub categories were examined by Jiang and Jain (2012) who provided a generalised version of the model.

2.1.3. Generalised Norton-Bass Model

While the Norton-Bass Diffusion Model takes into account multi-generational forms for a product or technology which expands on the initial model proposed by Bass (1969), does not differentiate between the generational adopters i.e. consumers that purchased a previous generation and are moving to the newer generation opposed to those consumers who are using the technology or product for the first time. The consumers who move from a previous generation to a newer one are referred to as switchers while the consumers that only purchase a technology or product for the first time after at least one previous generation was released or skip a generation are known as leapfroggers. This multi-generational model focuses on the adopters of the new technology or product i.e. switchers and leapfroggers, and not the change in adoption rates caused by the number of generational changes to a new product or technology, this modelling approach is therefore used to calculate the impact the switchers and leapfroggers have on the adoption rate at each generation. This technique is relevant to this research as mobile technologies have undergone several generations since inception in the 1980s and while this research focuses on the impact a generational change has on the adoption rate it is important to know why there is change in the adoption rate following a generational change. The descriptions of both the theoretical understanding and mathematical calculations for leapfroggers and switchers are given below.

Leapfroggers

Leapfroggers are consumers that will skip a generation in order to rather adopt the next generation. This may be due to factors such as cost, mobile subscribers were shown to show signs of being price elastic from previous research findings in the literature review, or that the earlier generations of the product or technology is not as appealing as later generations. With regards to mobile technology, an example could be that the earlier mobile phones were too big and costly, therefore people would rather use their landlines until the mobile products became cheaper and more practical to carry around. This is critical in understanding the adoption rate and the theory of innovators and adopters as it can explain the stage, lag and reasoning of when consumers decide to start using the technology or product. The calculations for leapfroggers from Jiang and Jain (2012) are shown in equations 37 up to and including 42.

Leapfrogging multiplier:

$$FG(t-\tau G) \tag{37}$$

Small time interval

$$[t-\ \varepsilon, t] \tag{38}$$

The number of leapfrogging adoptions during a small time interval.

$$m_1[F_1(t)-F_1(t-\varepsilon)]F_2(t-\tau_2) \tag{39}$$

∴ The rate of leapfrogging at time t, u_2(t)

$$U_2(t) = \lim_{\varepsilon\to 0}\frac{m_1[F_1(t)-F_1(t-\varepsilon)]F_2(t-\tau_2)}{\varepsilon} \tag{40}$$

$$m_1\mathcal{F}_1(F_2(t-\tau_2), \quad t \geq \tau_2 \tag{41}$$

The derivative of F_1(t) is the diffusion rate of G_1 at time t.

Comparing the number of leapfrogging adoptions from generation 1(G_1) to generation 2 (G_2) by time t.

$$U_2(t) = \int_{\tau_2}^{t} U_2(\theta)d\theta = m\int_{\tau_2}^{t} f_1(\theta)F_2(\theta-\tau_2)d\theta \tag{42}$$

While there are leapfroggers of the generations, there are also those consumers that will buy the previous generations' products and then buy the latter generations as well, these are referred to as switchers. The calculations for switchers provided by Jiang and Jain (2012) are shown in equations 43 up to and including 52.

Switchers

Consumers who bought a product from G_i and then bought a product from G_{i+1}

Rate of switching at time t:

$$w_2(t) = m_1F_1(t)f_2(t-\tau_2)\ , \qquad t \geq \ \tau_2 \tag{43}$$

Cumulative amount of switching at time t:

$$w_2(\tau) = \int_{\tau_2}^{t} w_2(\theta)d\theta = m\int_{\tau_2}^{t} f_1\theta f_2(\theta-\tau_2)d\theta \tag{44}$$

Rate of switching at time t = τ_2

$$w_2(\tau_2) = m_1F_1(\tau_2)f_2(0) \tag{45}$$

Existing adopters of G_1 at time τ_2

$$m_1F_1(\tau_2) \tag{46}$$

Instantaneous diffusion rate for G_2

$$f_2(0) \tag{47}$$

$\therefore$ All G_1 adopters are potential m_2 for G_2

When $t > \tau_2$ cumulative adoption

$$m_1F_1(t) - U_2(t)\ not\ m_1F_1(t) \tag{48}$$

Diffusion rate of G_2's unique potential for G_2

$$f_2(t-\tau_2) \tag{49}$$

Studies show that previous adopters will adopt at a faster rate than new adopters. Therefore, the switchers from G_1 to G_2 have a diffusion rate of

$$\left(\frac{m_1F_1(t)}{m_1F_1(t)-U_2(t)}\right)f_2(t-\tau_2) \tag{50}$$

This rate is referred to as the switching multiplier.

$$\therefore w_2(t) = [m_1F_1(t) - U_2(t)] * \frac{m_1F_1(t)}{m_1F_1(t)-U_2(t)} * f_2(t-\tau_2) \tag{51}$$

$$w_2(t) = m_1F_1(t)f_2(t-\tau_2) \tag{52}$$

Now that the equations to calculate both leapfroggers and switchers have been shown, the total adoptions for the first and second generations of the new product or technology can be calculated with these components in the models (Jiang & Jain 2012).

G_1 takes into account leapfroggers, but not switchers

$\therefore$ Noncumulative adoption rate for G_1

$$y_1(t) \tag{53}$$

$$m_1f_1(t) \quad when \quad t < \tau_2 \tag{54}$$

$$m_1f_1(t) - U_2(t) = m_1f_1(t)[1 - F_2(t-\tau_2)], \qquad t \geq \tau_2 \tag{55}$$

Cumulative adoption rate for G_1

$$Y_1(t) = m_1F_1(t) \quad when \quad t < \tau_2 \tag{56}$$

$$m_1f_1(t) - U_2(t) = m_1F_1(t) - m_1\int_{\tau_2}^{t} f_1(\theta)F_2(\theta-\tau_2)d\theta, \quad t \geq \tau_2 \tag{57}$$

G_2 takes into account leapfroggers and switchers

For G_2 there is only $t \geq \tau_2$ (58)

Adoption rate for G_2 is therefore:

$$y_2(t) = m_2 f_2(t - \tau_2) + U_2(t) + w_2(t) \tag{59}$$

$$y_2(t) = [m_2 + m_1 F_1(t)] f_2(t - \tau_2) + m_1 f_1(t) F_2(t - \tau_2) \tag{60}$$

Cumulative number of adopters of G_2:

$$Y_2(t) = m_2 F_2(t - \tau_2) + U_2(t) + W_2(t) \tag{61}$$

$$Y_2(t) = [m_2 + m_1 F_1(t)] F_2(t - \tau_2) \tag{62}$$

∴ The number of units in G_1 in use

$$S_1(t) = Y_1(t) - switchers \tag{63}$$

$$S_1(t) = Y_1(t) - W_1(t) \tag{64}$$

$$S_1(t) = m_1 F_1(t)[1 - F_2(t - \tau_2)] \tag{65}$$

The number of units in use for G_2

$$S_2(t) = Y_2(t) = [m_2 + m_1 F_1(t)] F_2(t - \tau_2) \tag{66}$$

Multi Generation Adoptions

After being able to calculate the adopters for the first and second generation, a multiple generation model can be formulated in order to perform the calculation for the number of adopters for several generations of a product or technology (Jiang & Jain 2012).

Adoption rate for G_i

$$\tilde{y}_1(t) = m_1 f_1(t) \; when \; t \geq 0 \tag{67}$$

$$\tilde{y}_i(t) = [m_i + \tilde{y}_i - (t)] f_i(t - \tau_i) + \tilde{y}_{i-1}(t) F_i(t - \tau_i) \;\; when \; t \geq \tau, i \geq 2 \tag{68}$$

Cumulative adoptions for G_i

$$\tilde{Y}_1(t) = m_1 F_1(t) \qquad when \; t \geq 0 \tag{69}$$

$$\tilde{Y}_i(t) = [m_i + \tilde{Y}_{i-1}(t)] F_i(t - \tau_i) \quad when \; t \geq \tau_i, i \geq 2 \tag{70}$$

Leapfrogging rate for G_i

$$u_{i+1} + (t) = \tilde{y}_i(t) F_{i+1}(t - \tau_{i+1}), \;\; t \geq \tau_{i+1} \tag{71}$$

Cumulative leapfroggers

$$U_{i+1}(t) = \int_{\tau_{i+1}}^{t} u_{i+1}(\theta)d\theta \tag{72}$$

Switching at G_i

Switching rate

$$w_{i+1}(t) = \tilde{Y}(t)f_{i+1}(t-\tau_{i+1}), \quad t \geq \tau_{i+1} \tag{73}$$

Cumulative number of switchers

$$W_{i+1}(t) = \int_{t+1}^{t} w_{i+1}(\theta)d\theta \tag{74}$$

Adoption rate for generation i

$$(1 < i < N) \tag{75}$$

$$\tilde{y}_i(t), \quad \tau_i \leq t \leq \tau_{i+1} \tag{76}$$

$$\tilde{y}_i(t) - u_{i+1}(t), \quad t \geq \tau_{i+1} \tag{77}$$

Cumulative adoptions for G_i

$$\tilde{Y}_i(t), \qquad \tau_i \leq t \leq \tau_{i+1} \tag{78}$$

$$\tilde{Y}_i(t) - U_{i+t}(t), \quad t \geq \tau_{i+1} \tag{79}$$

Adoption rate for final generation

$$y_N(t) = \tilde{y}_N(t), \qquad t \geq \tau_N \tag{80}$$

Cumulative adoptions for final generation

$$Y_N(t) = \tilde{Y}_N(t), \quad t \geq \tau_N \tag{81}$$

∴ The number of units in use per generation is

$$S_i(t) = Y_i(t) - W_{i+1}(t) \tag{82}$$

$$S_i(t) = \tilde{Y}_i(t)[1 - F_{i+1}(t - \tau_{i+1})], \quad i < N \tag{83}$$

$$S_N(t) = Y_N(t) = \tilde{Y}_N(t) \tag{84}$$

The augmented model, the Generalised Norton-Bass Model, for the original Bass Diffusion Model can now understand the mix of adopters at different stages of the adoption cycle by adding not only a generational component to the model, but also being able to understand the type of adopter at each generational change of the product or technology. This shows that even though there may be an improvement in the technology or product, sales or adoption rates may not increase due to previous generational adopters as well as non-adopters not seeing enough increased utility to upgrade or become initial adopters, and they would rather wait for future generational improvements before upgrading or adopting the technology or product. There would also be consumers who do believe the improved utility from the new generation of the product or technology is worth upgrading to. While price was not examined in these models and is not be examined in this research other than the price elasticity characteristics of mobile phone and internet users, it could definitely impact the adoption rate of a new generation of a technology or product, as a small improvement in the technology which carries a high price tag may not be viewed as worth adopting.

While the additions of generational and type of adopters has added more explanatory power to the model it still lacks inputs from external factors such as the economic environment and the demographics for the population of potential adopters. In this research each grouping of potential adopters consists of a country's population as the statistics are available by the World Bank database at this level. Previous research taking these economic and demographic factors into account by Gelper and Stremersch (2014) will now be looked at and their methodology for testing those factors used.

2.1.3. Economic Variable Selection

Bass (1969) showed the importance of understanding the adopters of the new technology or product, and if there are more innovators than imitators there will be faster rates of adoption. Norton and Bass (1987) showed that the generational changes for a product or technology were also shown to play a role in the adoption rate. Jiang and Jain (2012) took it a step further by explaining that while some may adopt the technology and then upgrade with the new generation of it - switchers - and some may skip generations – leapfroggers - as they do not see the trade-off of purchasing the new generation of the product or technology being worth the price or effort to acquire it and would rather wait for future generations of the good. While these models gave a basic understanding of adoption rate they do not take into account external economic factors that may impact the rate of adoption such as: the GDP growth rate, the exchange rate, the unemployment rate and political unrest. Further analysis of the adopters such as urbanisation of a population and the age of a population were also not examined by the models. This leaves an incomplete view of the adoption rate, but this was addressed by Gelper and Stremersch (2014) in which various economic variables were viewed.

This research leverages the work of Gelper and Stremersch (2014) to understand how to calculate the impact that demographic and economic variables have on the adoption rate of a new product or technology, as well as using the variables they used as a guideline for the variables that will be selected to understand the adoption rate of mobile user penetration and internet user penetration for a country. The methods used by Gelper and Stremersch (2014) to test various economic variables were Bayesian Lasso and Bayesian Elastic Net models. Gelper and Stremersch (2014, p.357) explained that these methods are ideal for sparse data that contains numerous variables, but few data points. These models were achieved by specifying an appropriate informative prior, which leads to a specific form of Bayesian Regulization.

Variables that were found to be important by Gelper and Stremersch (2014, p.363) are:

- Economic wealth, as it impacts all three parameters, being the market potential (m), innovation coefficient (q) and imitation coefficient (p), of the Bass Diffusion Model.

- Education, which impacts the market potential (m) and the innovation coefficient (p).
- Income inequality that impacts market potential (m).
- Economic openness, which impacts the innovation coefficient (p).
- Mobility, impacting the imitation coefficient (q).

Variable Selection Methodology

Gelper and Stremersch (2014) used a Penalized Likelihood and Bayesian Regulization method in their models. The steps performed by Gelper and Stremersch (2014) are shown in equations 85 up to and including 101.

Multiple linear regression model

$$y = Xb + e \tag{85}$$

When the response vector is y and X is the (N × k) matrix containing k regressors. The assumption is that the response is to be mean-centered and the regressors to be standardized so that no intercept will be included. Also, let $b = (b_1,\ldots, b_k)'$ denote the vector of regression coefficients. Another assumption is that the error term e follows a N(0, σ_e^2) distribution, and the penalized likelihood estimator maximizes the likelihood under a constraint on the coefficients (Gelper & Stremersch 2014, p.358).

The penalized likelihood estimator maximises the likelihood under a constraint on the estimated parameters towards zero.

The form of the penalized estimators:

$$\hat{b} = arg \min_b \sum_{i=1}^{N} (y_i - X_i b)^2 \;\; subject\ to \tag{86}$$

$$(1-\propto) \sum_{j=1}^{k} |b_j| + \propto \sum_{j=1}^{k} b_j^2 < t \quad (equation\ 2) \tag{87}$$

$$t > 0 \tag{88}$$

$\propto = 1$, Ridge estimator puts a constraint on the sum of squared coefficients.

$\propto = 0$, Lasso estimator puts a constraint on the absolute values of the coefficients.

$0 < \propto < 1$, Elastic Net estimator puts a constraint on the coefficients that is a combination of the Ridge and Lasso constraints.

Gelper and Stremersch (2014, p.365) explained that Ridge regression does not result in the variable selection. The Ridge regression will only rarely result in a zero coefficient estimates situation. The Lasso solution is generally more stable than the Ridge solution. The difference between the Lasso and Elastic Net is that the Elastic Net generally chooses strongly correlated variables jointly in or out of the model. This is called the Grouping Effect. When in an example the Elastic Net method chooses to select together two correlated variables, the Lasso method would only select one variable. For this reason this research will only use the Lasso regression method out of the Lasso, Ridge and Elastic Net methods.

Gelper and Stremersch (2014, p.359) go on to show the solution to equations 86, 87 and 88 whereby they have a Bayesian interpretation.

Bayesian Ridge specifies a normal prior given by:

$$b|\sigma_e^2, \lambda_r^2 \sim N(0, \frac{\sigma_e^2}{\lambda_r^2} I_k) \tag{89}$$

Prior mean for all regression parameters are 0. The shrinkage parameter λ_r^2 controls the precision of the prior. A more accurate posterior is calculated for longer values of the shrinkage parameter. Taking the prior mean equal to zero in combination with a tight prior is a conservative choice. If after combination with the data the posterior of a parameter is located away from zero, the corresponding repressor is important in the model.

A prior specification for the shrinkage parameter:

$$\lambda_r \sim Gamma(r_r, s_r) \tag{90}$$

And for the error variance

$$\sigma_e^{-2} \sim Gamma(U_r, V_r) \tag{91}$$

The Bayesian Ridge method is not good for modelling data with multicollinearity, which economic data variables can have. Therefore, the Lasso regression will need to be used if there is multicollinearity.

Lasso point estimator for

$$y = Xb + e \tag{92}$$

Is the mode of the posterior density of the regression parameters when imposing an independent Laplace prior with mean zero on the regression coefficients:

$$b_j|\sigma_e^2, \lambda_1 \sim Laplace\left(0, \frac{\sigma_e}{\lambda_1}\right) = \frac{\lambda_1}{2\sigma_e} \exp(\frac{-\lambda_1}{\sigma_e}|b_j|) \tag{93}$$

The term $|b_j|$ facilitates variable selection

The key to variable selection using this procedure is that depending on the value of the shrinkage parameter, the posterior mode of some regression coefficients can become exactly zero (Gelper & Stremersch 2014, p.359). Whether the posterior mode of a regression coefficient is zero or not has an important consequence for model interpretation (Gelper & Stremersch 2014, p.359). Because the mode will always be included in the highest posterior density region, a regression parameter with zero posterior mode will never be significant (Gelper & Stremersch, 2014, p.360). The Laplace prior reflects the fact there are many small effects and a number of important effects due to it putting more prior mass close to zero and in the tails when compared with a normal prior (Gelper & Stremersch, 2014 p.360). Other variable selection models assume that some of the variables are equal to zero, which is problematic as that is probably not the case when looking at which economic factors impact on the rate of diffusion. Elastic Net prior on the regression coefficients is a compromise between the Gaussian prior of Ridge regression and the Laplace prior of the Lasso.

$$p(b_j|\sigma_e^2, \lambda_{1n}, \lambda_{2n} \propto \exp(-\frac{1}{2\sigma_e^2}(\lambda_{1n}|b_j| + \lambda_{2n} b_j^2)) \tag{94}$$

Gelper and Stremersch (2014, p.360) showed the Bayesian representation of the international Bass Diffusion Model in equations 95 up to and including 101.

$S_{ij}(t)$ = penetration level of product j in country I at period t after commercialization.

$$\therefore S_{ij}(t) = \left(p_{ij} + q_{ij}\ \frac{s_{ij}(t-1)}{m_{ij}}\ \right)\left(m_{ij} - S_{ij}(t-1)\right) + \varepsilon_{ij}(t) \tag{95}$$

$$where\ \ \Delta S_{ij}(t) = S_{ij}(t) - S_{ij}(t-1) \tag{96}$$

$$and\ \varepsilon_{ij} \sim N(0, \sigma_j^2) \tag{97}$$

$m_{ij}\ is\ market\ potential$

$P_{ij}\ is\ market\ potential$

$q_{ij}\ is\ market\ potential$

For product j in country i

$m_{ij}, p_{ij}\ and\ q_{ij}$ are first decomposed by country and product after controlling for the product-country specific lag denoted by L_{ij}.

Denote the vector of Bass Model parameters for products j in country i by $\theta_{ij} = (m_{ij}, p_{ij}, q_{ij})$

Then the variance decomposition

$$logit(\theta_{ij}) = \propto_i + \beta_j + \gamma L_{ij} + \varepsilon_{ij}\ \ with\ \ \varepsilon_{ij} \sim N(0, \textstyle\sum_e) \tag{98}$$

Where a full covariance matrix, $\sum_\varepsilon$, is allowed.

The values $\theta_{ij} = (m_{ij}, p_{ij}, q_{ij})$ are between zero and one. This means a logit transformation is needed to calculate values on the whole real line.

The first component of the ϒ vector is fixed at zero because the introduction lag only affects the growth rate towards the market potential (determined by $p_{ij}\ and\ q_{ij}$) and not the market potential m_{ij} itself. The vector $\propto_i$ is regressed on country characteristics represented by the matrix X that has the dimensions (x * (the number of countries) * k (the number of country characteristics))

3rd level of the Bass Diffusion Model

$$\propto_i = X_i\delta + \eta_i\ \ \ \ with\ \ \eta_i \sim N(0, \Sigma_\eta) \tag{99}$$

X_i is the row vector of length k with country characteristics for country i.

Matrix δ (k*3) captures the effect of the country characteristics of the diffusion process. Matrix δ is estimated using Bayesian Regularization and shows the effect a country characteristics has on the diffusion pattern.

β_j parameter vector shows the product-specific effects. It is modelled as a random effect with mean zero (for identification).

$$\beta_j \sim N(0, \Sigma_\beta) \tag{100}$$

$$\Sigma_\eta \quad and \quad \Sigma_\beta \quad is\, diagonal \tag{101}$$

Using the Markov Chain Monte Carlo (MCMC) draws, the posterior evaluation of parameters can be calculated.

The Lasso and Elastic Net case, apart from the posterior MCMC draws, selection of the coefficients for the regression in δ is found by using the mode (Gelper & Stremersch 2014, p.361). Mode is found by using a maximum posterior (MAP) estimation. Rao-Blackwellization is used to find the MAP estimator. Each draw in the MCMC chain has its conditional distribution of δ stored on a fine grid. For both Lasso and Elastic Net the conditional distribution is orthant normal and can sometimes have a zero-mode due to the shape of the prior (Gelper & Stremersch 2014, p.361). An average of the stored conditionals over the MCMC draws for each grid point is used to get the estimate of the marginal posterior from which the mode can be obtained in order to get the point estimates for the Lasso or Elastic Net point estimates (Gelper & Stremersch 2014, p.361).

In order to augment the Bass Diffusion Model, numerous variables were considered for inclusion in the model such as: age of population, unemployment rate, access to electricity, urbanisation, conflicts domestically and in the region, literacy rates and natural disasters. These variables were viewed in order to leverage off of the research by Gelper and Stremersch (2014). The generational changes of mobile technology were also added in the models as a variable to test whether the changes in technology show a statistical significance and agree with the research completed by Bass and Norton (1987) and, Jiang and Jain (2012). If it can be shown that there is a statistically significant relationship between the economic, demographical and generational variables with both mobile user penetration and internet user penetration globally it would validate the previous findings by Gelper and Stremersch (2014), Bass and Norton (1987) and, Jiang and Jain (2012). This would open the possibilities to create a model that can be generalised and used for future technologies.

The reason that the Bayesian Lasso regression and the Stepwise OLS regression methods were both used is because the Bayesian Lasso regression method improves the prediction accuracy and interpretability of regression models by choosing the variables that are the most important instead of keeping all the variables, therefore giving a more condensed model. Before the Bayesian Lasso regression method, the most commonly used method for choosing which variables to include was stepwise selection, however it only improves prediction accuracy in specific cases, such as when only a few variables have a strong relationship with the outcome, but in other scenarios it can make prediction error worse. With that being said, firstly the Stepwise OLS regression method will be used to test the variables relationship with mobile and internet user penetration followed by the Bayesian Lasso regression as used in the research by Gelper and Stremersch (2014). This will mean improved results when using the Stepwise OLS regression method when there are only the variables that have a strong relationship with the outcome and improved results when using the Bayesian Lasso regression method for cases where there are not only a few covariates that have a strong relationship with the outcome.

2.2. Data

In the 59 country sample set there are 44 developing countries and 15 developed countries. The countries were chosen based on whether they have the available data needed for analysis. The reason for the disproportional number of developing countries when compared to developed countries is due to there being far fewer developed countries when compared to the number of developing countries. The date range for the analysis was between and including the years 1995 to 2015, which were chosen as at the time of data collection, 2015 was the latest year for the data and 1995 was chosen because it was the year the data started becoming frequently populated.

Region	**Number of Countries**
Africa	18
Asia	9
Western Europe	8
Eastern Europe	8
South America	5
Middle East	5
North America	2
Australasia	2
Central America	2
Total	59

Table 2.2.1. 59 country data sample by countries in region

The data was collected from the World Bank Economic Development Indicators database, financial statements of telecom companies and telecom regulators databases. The metric used for political and economic stability as well as warfare/conflict is based on a scale of 1 to 5, 1 being politically and economically stable with no conflict and 5 being politically and economically unstable with widespread conflict. This metric is quantitative, but decided by the researcher when looking at the overall environment of the country. This scaling from 1 to 5 needs to be comparative where the scaling compares countries i.e. Syria will have a much higher rating than Switzerland for the year 2014 due to the civil war in Syria for that year. This may not be exactly quantitatively calculated, but it does help in providing information on whether large differences between countries with regards to the overall environment of the country’s political, economic or social environment climate impacts the rate of adoption for new technologies or products. Key metrics collected were mobile users per 100 people, internet users per 100 people, GDP per capita in current USD, unemployment rate of total labour force, year on year inflation rate, age of population, country development status, urbanisation levels of a country, exchange rate compared to USD, and generation of available mobile technology globally.

The target variables of mobile and internet penetration trend upwards and needed differencing to make the models useable. The variables in the models were differenced once by using percentage changes year on year for each variable to make the model stationary. While some of the independent variables may have already been in percentage changes year on year and others being nominal figures, using percentage changes to difference the nominal figures to percentage changes worked by showing that the pace of changes are increasing or decreasing and making all the variables into percentage differences so they can be compared. This will show as a percentage increase or decrease in the independent variable leads, to a percentage increase or decrease in the adoption rate. The findings of the models, graphical analysis of the data and the variables that need to be added to the Bass Diffusion Model will be viewed in the next chapter.

3. Empirical Results

3.1. Initial Findings

Tables 3.1.1. to 3.1.3 compare the average GDP per capita in current USD against which level of mobile penetration the country falls into. At levels below 100% of mobile penetration there are clear positive correlations between GDP per capita and mobile penetration for developing countries. This correlation breaks down after 100% mobile penetration. Developed countries tend to have higher GDP per capita and mobile penetration rates. It is not clear that within the developed country grouping that there is a positive correlation between GDP per capita and mobile penetration, but the higher rates of mobile penetration when compared to developing countries may be due to GDP per capita in current USD only increasing mobile penetration up to a certain threshold before it stops being a positively significant variable.

Year: 1995	**GDP Per Capita in Current USD**	
Mobile Penetration Bands	**Developed**	**Developing**
0-10%	25 984	1 975
10-20%	25 339	-
20-30%	32 395	-
Average	**26 710**	**1 975**

Table 3.1.1. 1995 Mobile Penetration Percentage and GDP Per Capita in Current USD by Country Development Status

Year: 2005	**GDP Per Capita in Current USD**	
Mobile Penetration Bands	**Developed**	**Developing**
0-10%	-	405
10-20%	-	1 456
20-30%	-	2 067
30-40%	-	4 561
40-50%	-	3 917
50-60%	36 190	7 401
60-70%	44 308	4 707
70-80%	36 049	6 736
80-90%	26 802	28 406
90-100%	43 064	-
100-110%	50 462	-
110-120%	-	-
120-130%	39 240	3 831
Average	**26 710**	**1 975**

Table 3.1.2. 2005 Mobile Penetration Percentage and GDP Per Capita in Current USD by Country Development Status

Year: 2015	GDP Per Capita in Current USD	
Mobile Penetration Bands	**Developed**	**Developing**
0-10%	-	-
10-20%	-	-
20-30%	-	348
30-40%	-	-
40-50%	-	590
50-60%	-	574
60-70%	-	584
70-80%	-	1 498
80-90%	43 316	3 590
90-100%	-	5 368
100-110%	31 105	6 456
110-120%	49 946	3 660
120-130%	38 869	6 514
130-140%	62 785	2 033
140-150%	30 049	9 386
150-160%	-	19 725
160-170%	-	6 532
170-180%	-	20 733
180-190%	-	10 510
Average	**46 018**	**6 363**

Table 3.1.3. 2015 Mobile Penetration Percentage and GDP Per Capita in Current USD by Country Development Status

Tables 3.1.4 to 3.1.6. show the average GDP per capita in current USD grouped by development status with respect to their associated internet user penetration bands for the years 1995, 2005 and 2015. With mobile penetration there was only a clear positive correlation relationship between GDP per capita and mobile penetration for developing countries and up to a certain threshold. With internet user penetration the positive correlation holds for both developed and developing countries with no easily identifiable threshold where this relationship breaks down.

Year: 1995	GDP Per Capita in Current USD	
Internet Penetration bands	**Developed**	**Developing**
0-10%	26 700	1 975
10-20%	26 851	-
Average	**26 710**	**1 975**

Table 3.1.4. 1995 Internet Penetration Percentage and GDP Per Capita in Current USD by Country Development Status

Year: 2005	GDP Per Capita in Current USD	
Internet Penetration bands	**Developed**	**Developing**
0-10%	-	1 459
10-20%	-	5 443
20-30%	-	16 408
30-40%	31 959	7 818
40-50%	30 695	-
50-60%	-	-
60-70%	35 598	-
70-80%	37 788	-
80-90%	55 370	-
Average	**39 240**	**3 831**

Table 3.1.5. 2005 Internet Penetration Percentage and GDP Per Capita in Current USD by Country Development Status

Year: 2015	GDP Per Capita in Current USD	
Internet Penetration bands	**Developed**	**Developing**
0-10%	-	739
10-20%	-	831
20-30%	-	2 587
30-40%	-	4 431
40-50%	-	2 833
50-60%	-	7 174
60-70%	30 049	11 720
70-80%	40 945	8 447
80-90%	46 267	-
90-100%	50 891	66 347
Average	**46 018**	**6 363**

Table 3.1.6. 2015 Internet Penetration Percentage and GDP Per Capita in Current USD by Country Development Status

Figure 3.1.1. Shows that the inflation rates for developing countries on average are higher than that of developing countries for the period 1995 to 2015. While developed countries have kept their inflation rates relatively stable over the analysed period, developing countries inflation rates have been more volatile. Between 1995 and 2001 the average inflation rate of developing countries was greater than 10% on average.

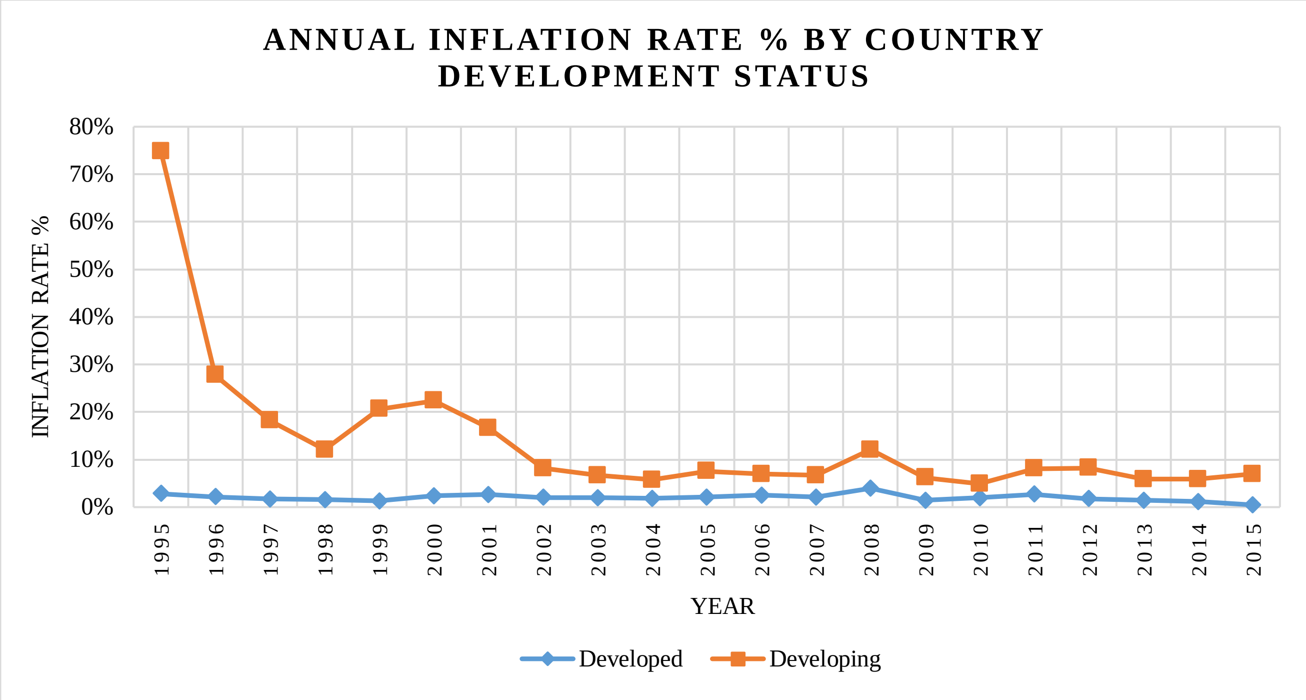

Figure 3.1.1 Average Inflation by Country Development Status

Figure 3.1.2. Shows average unemployment rates over the period 1995 to 2015 grouped by a countries development status. The period 1999 to 2008 saw a divergence of unemployment rates between developed and developing countries. Over this period, developed countries kept their unemployment rates between 7% and 5% while developing countries reached 9% on average before dropping 8% by 2007. Since 2008 unemployment rates on average have remained within a 1% difference between developed and developing countries.

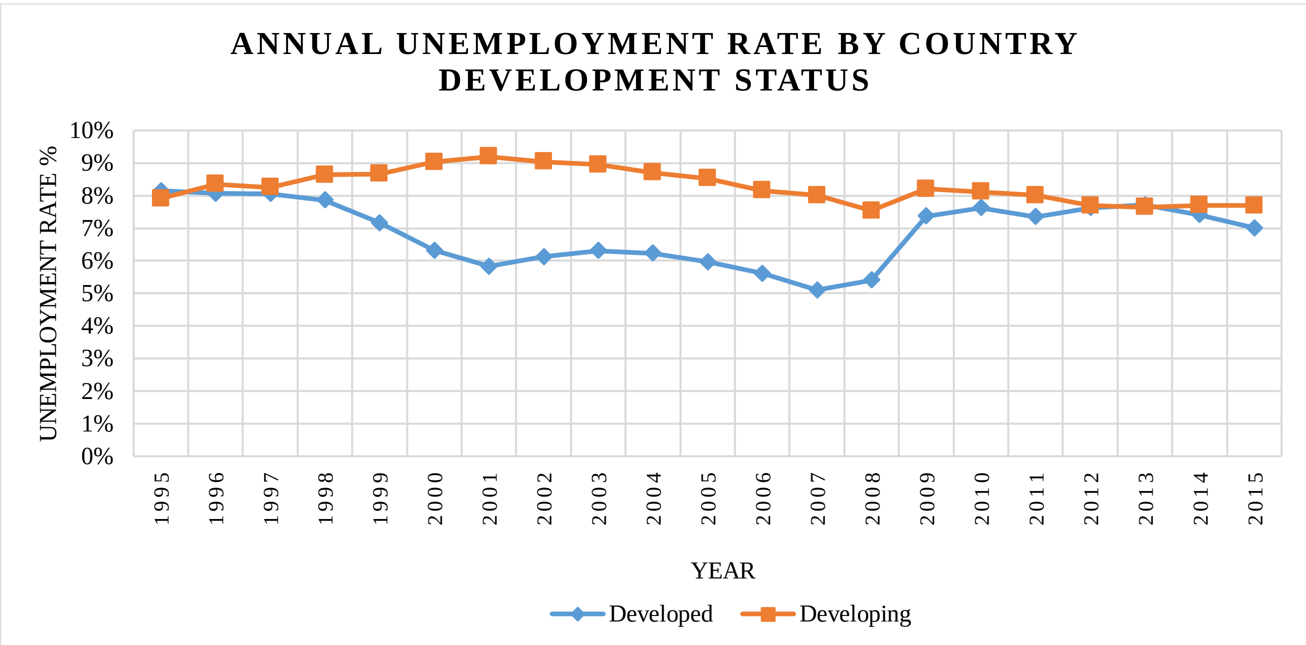

Figure 3.1.2. Annual Unemployment Rate by Country Development Status

Figure 3.1.3. Views the average percentage of the total population that is of working age. This indicates how much of the total population are the right age to join the workforce, earn a salary and be consumers. Across

the period 1995 to 2015, developed countries on average have a higher portion of their total population in the working age group when compared to developing countries. Developed countries are seeing a decline in working age population while developing countries are seeing their working age population as a percentage of their total populations grow.

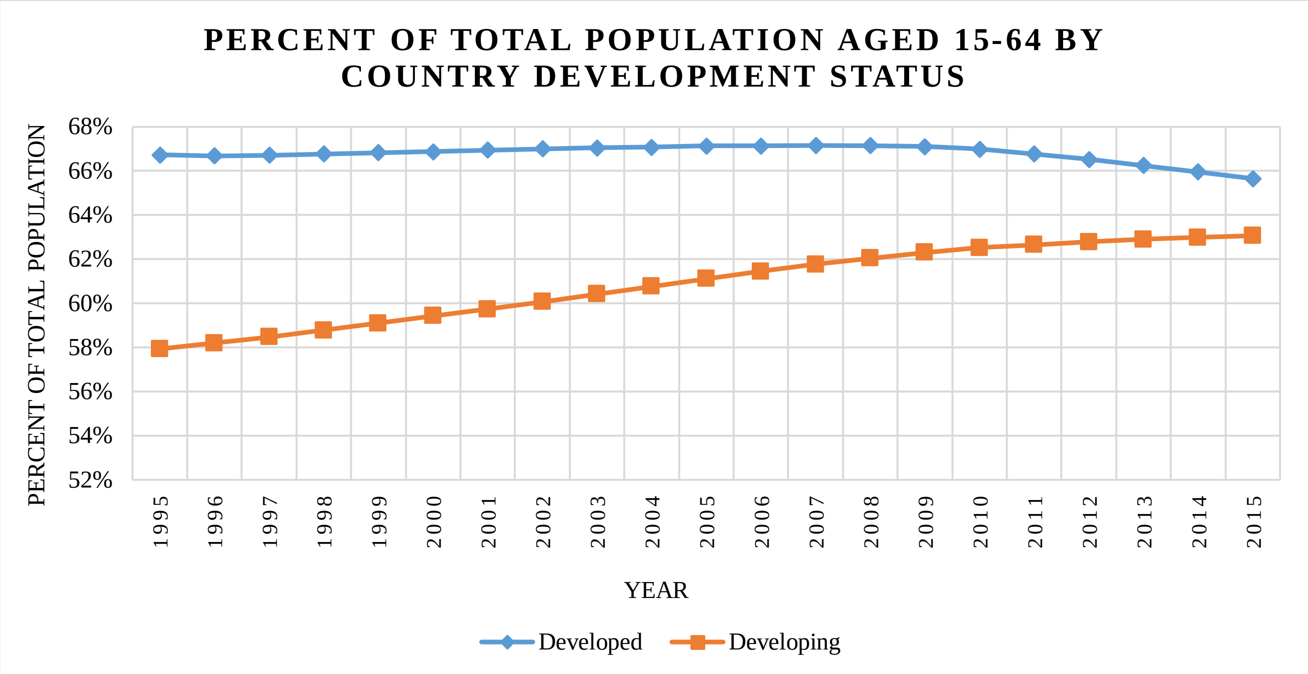

Figure 3.1.3. Percent of Total Population Aged 15-64 by Country Development Status

Figure 3.1.4. Shows that developed countries on average have a higher portion of their total population living in urban areas when compared to developing countries. Both developed and developing countries populations are showing an upward trend towards urbanisation over the period 1995 to 2015.

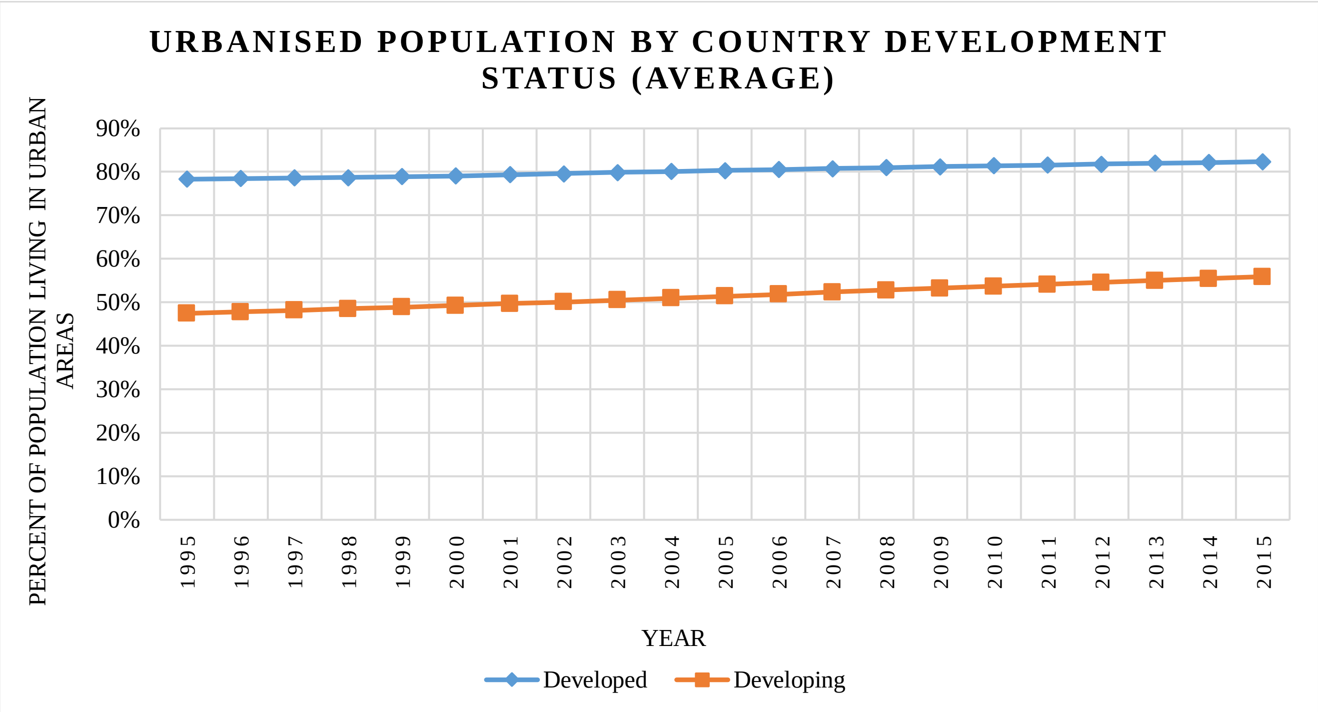

Figure 3.1.4. Percent of Total Population who live in Urban Areas by Country Development Status

Figure 3.1.5. Shows that the GDP Per Capita in current USD is significantly higher on average for developed countries when compared against developing countries over the period 1995 to 2015. Both developed and developing countries have seen an increase in GDP Per Capita in current USD on since 2001 with few years seeing significant (5 percentage) decreases year on year with exceptions being the years 2009 and 2015.

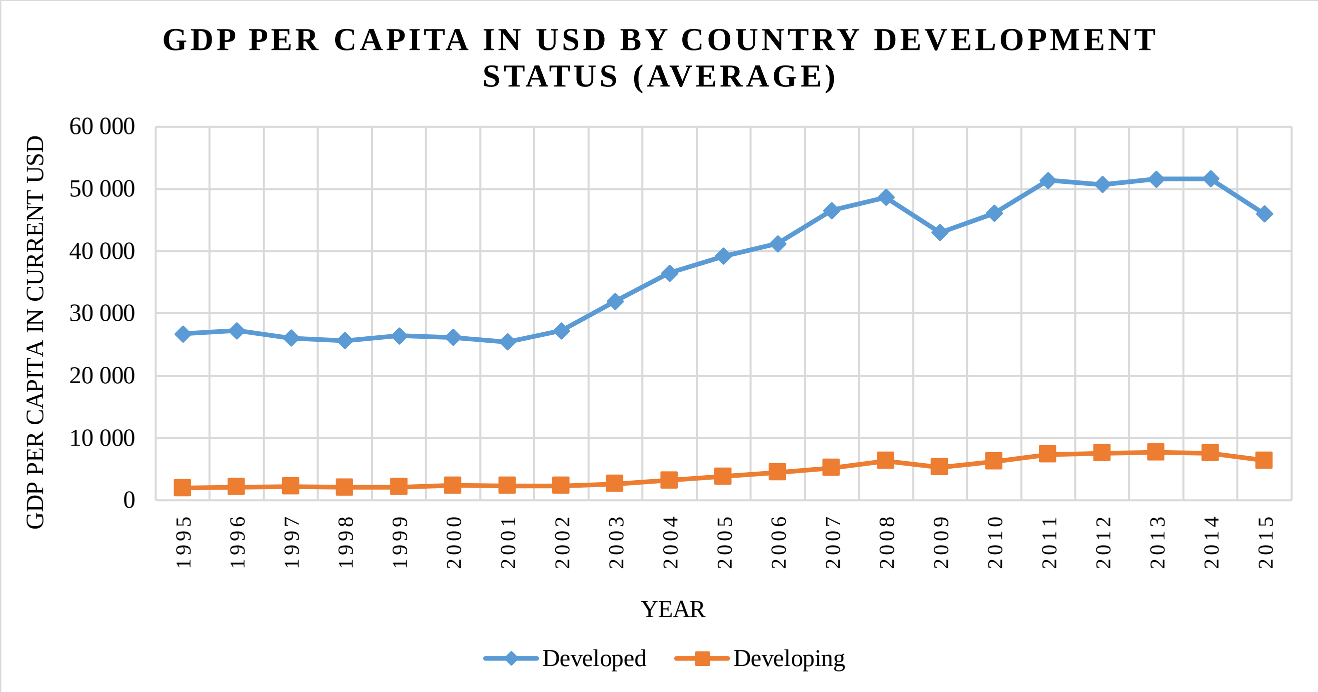

Figure 3.1.5. GDP per capita in current USD by Country Development Status

Developed countries had higher mobile penetration rates from the start and throughout the 20-year period of analysis when looking at the averages across countries. While both follow the S shaped curve theorised by the Bass Diffusion Model, developed countries have a much shorter first period when compared with their developing country counterparts. In the Bass Diffusion Model, the reasoning for this is due to there being innovators and imitators, however there may be other factors that influence this rate of adoption. These other factors may be economical, demographical or because of political reasons.

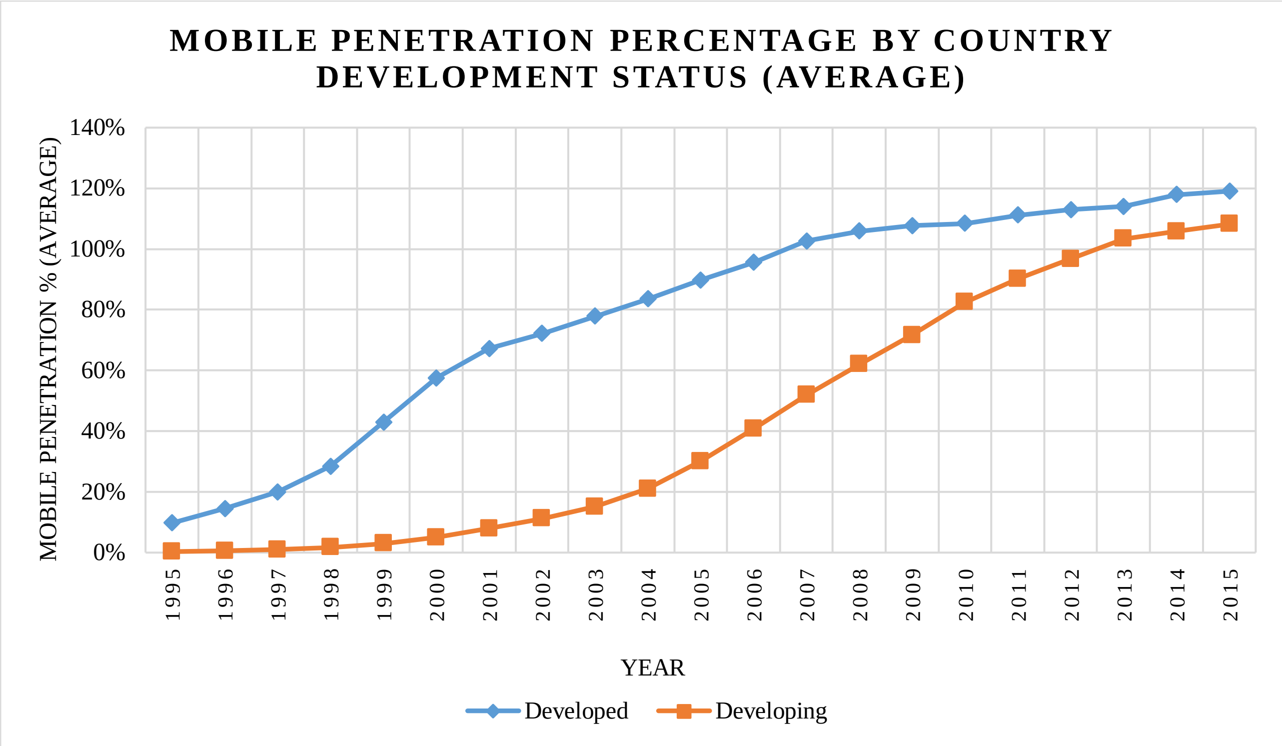

Figure 3.1.6. Mobile Penetration Percentage by Country Development Status

Developed countries had higher internet user penetration rates from the start and throughout the 20-year period of analysis when looking at the averages across countries. While the developed countries follow the S shaped curve theorised by the Bass Model, developing countries follow more of a gradually increasing linear curve. Due to the stage of adoption at the cut-off date point, developing countries may still follow the S-shaped curve, but spread out over a longer time frame when compared to its developed peers. In the Bass Diffusion Model, the reasoning for this is due to there being innovators and imitators, however there may be other factors that influence this rate of adoption. These other factors may be economical, demographical or political. Factors such as network effects can also impact the adoption rate i.e. social networks. The technology that allows for mobile internet usage only started becoming adopted by mobile devices around the period of the late 1990s therefore, due to the high cost of first-generation products there would have been a lag before the more price elastic developing country populations would have been able and willing to buy mobile devices that have these capabilities. Products that were able to use voice services had been available for at least 10 years before the first date used in this analysis, 1995, and therefore, would have had time for the price to come down for those products and lead to the higher adoption rates in this analysis.

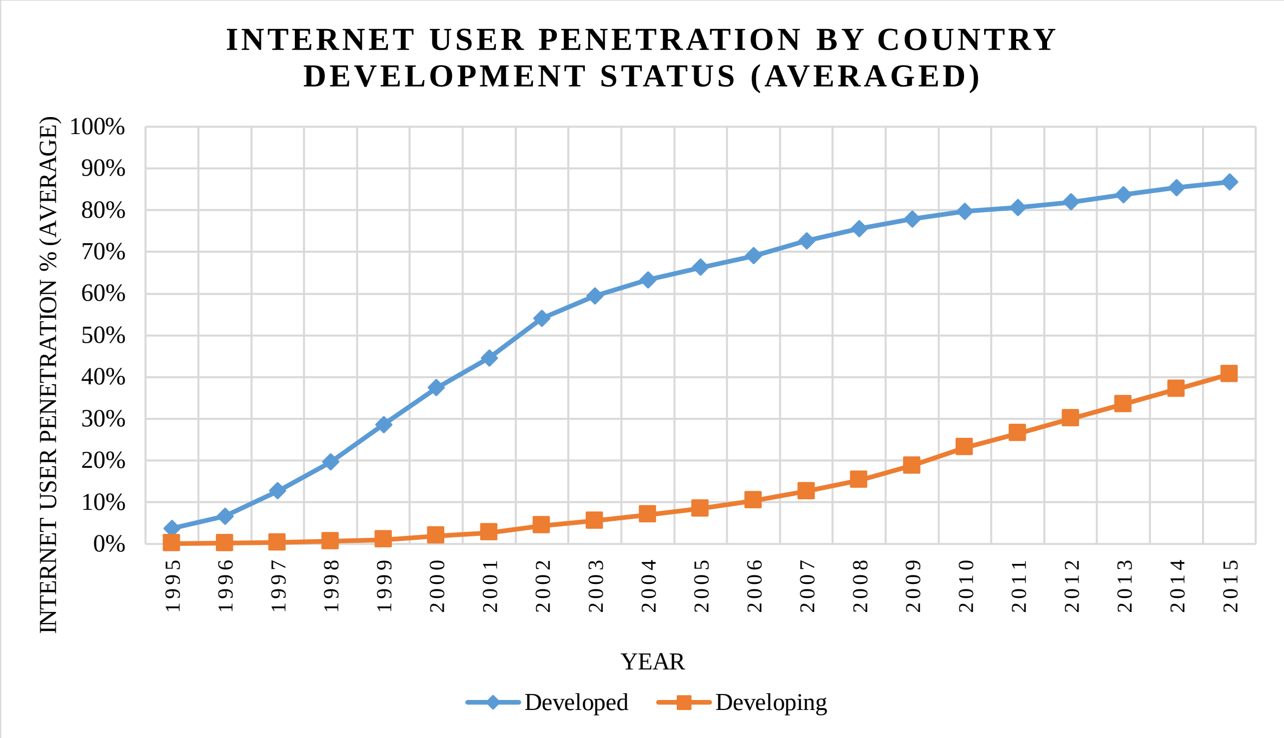

Figure 3.1.7. Internet User Penetration by Country Development Status

The more developed regions of Western Europe, Australasia and Northern America had the highest mobile penetration rates in the first 15 years (1995 to 2010). From 2010 there is a convergence in the mobile penetration rates between the regions.

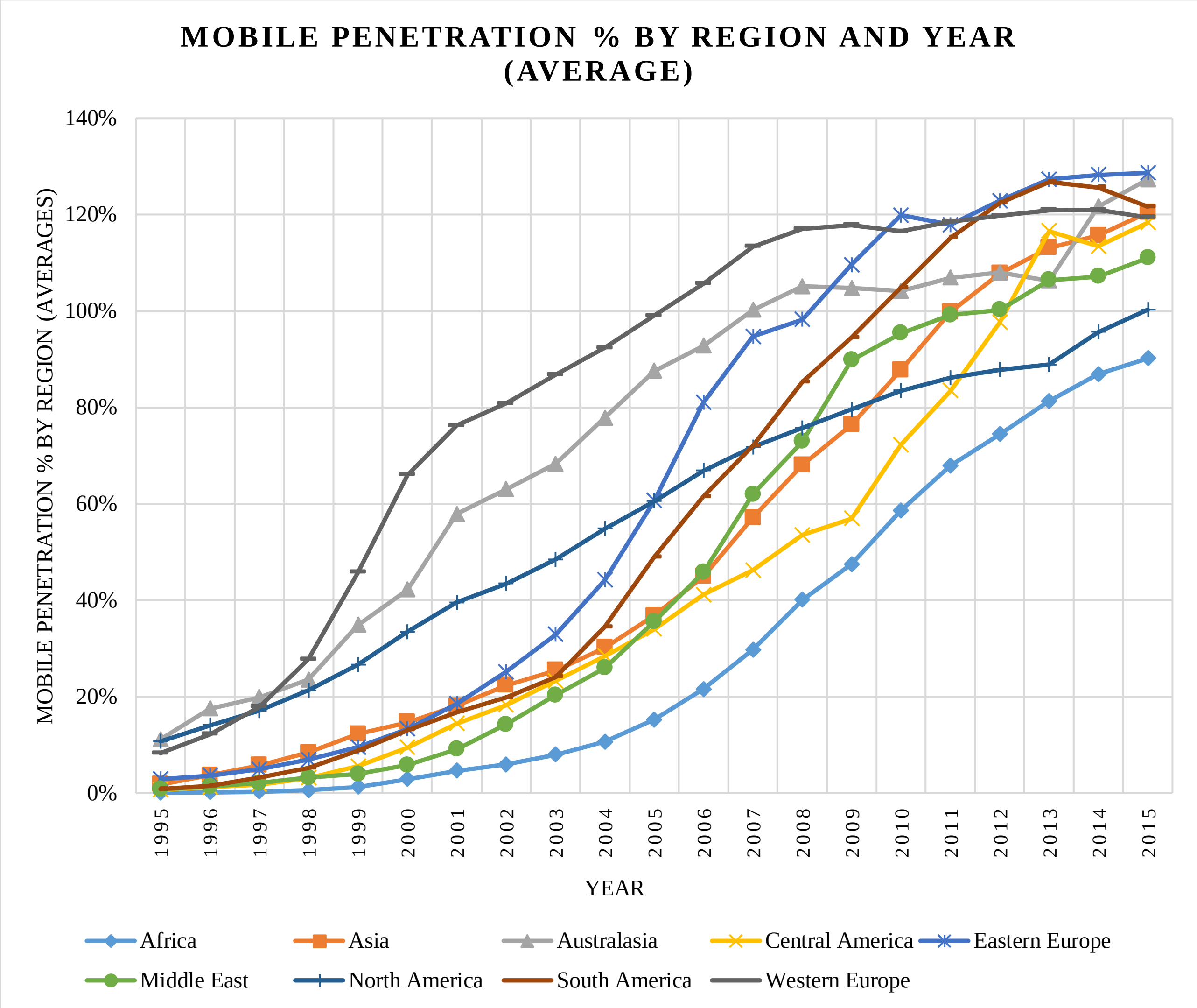

Figure 3.1.7. Mobile Penetration % by Region and Year

There are larger gaps in penetration rates between the regions when comparing mobile penetration rates against internet penetration rates between the periods 1995 to 2015. This reflects the differences in internet user penetration between the developed and developing countries, and the delayed convergence of access to internet services.

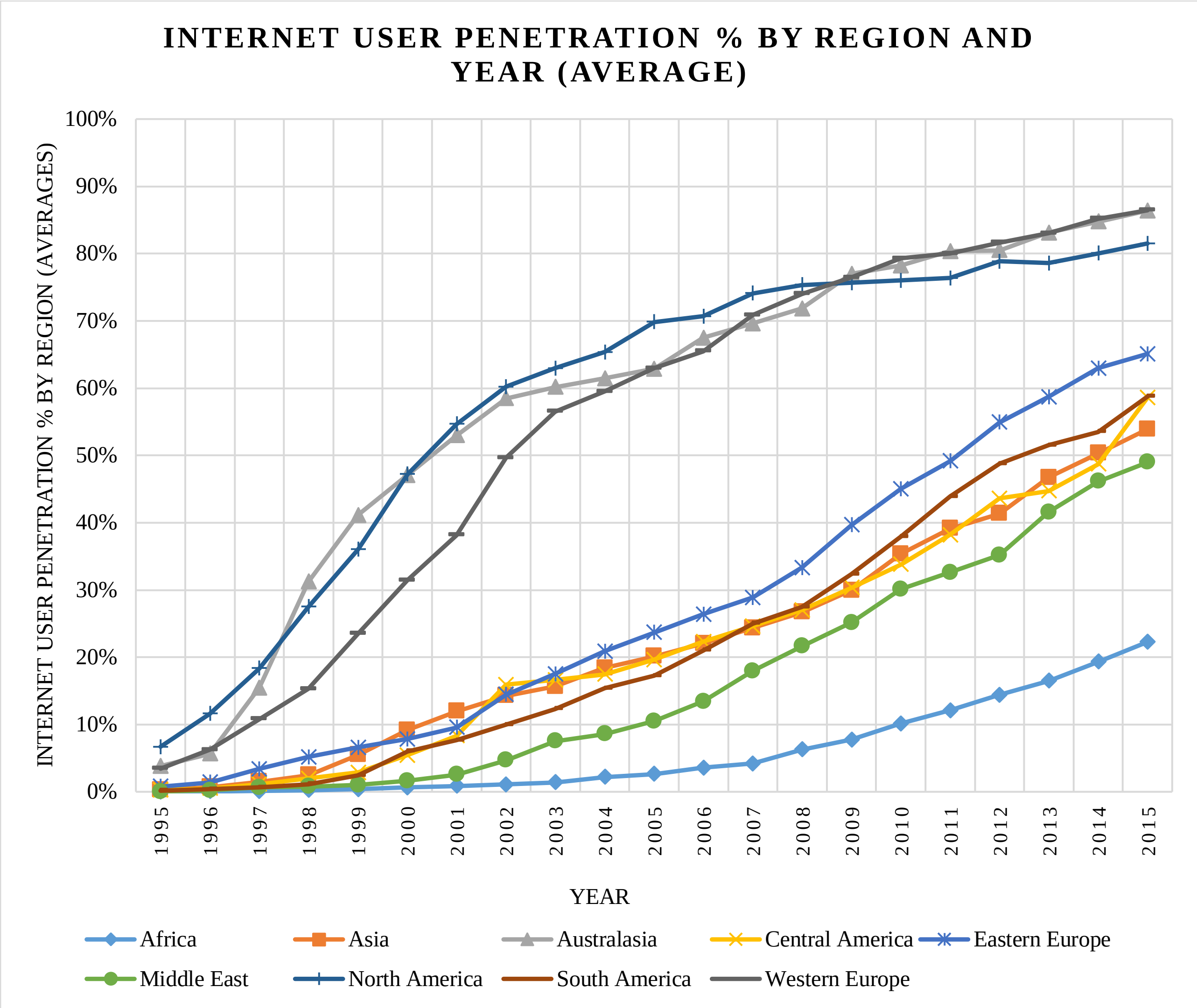

Figure 3.1.8. Internet User Penetration % by Region and Year

Mobile penetration rates across all the countries when averaged is higher than internet user penetration rates over the period 1995 to 2015. The mobile penetration rates across all countries when averaged follows a similar S shaped curve to the one theorised in the Bass Diffusion Model, while internet user penetration rates follow an increasing linear line.

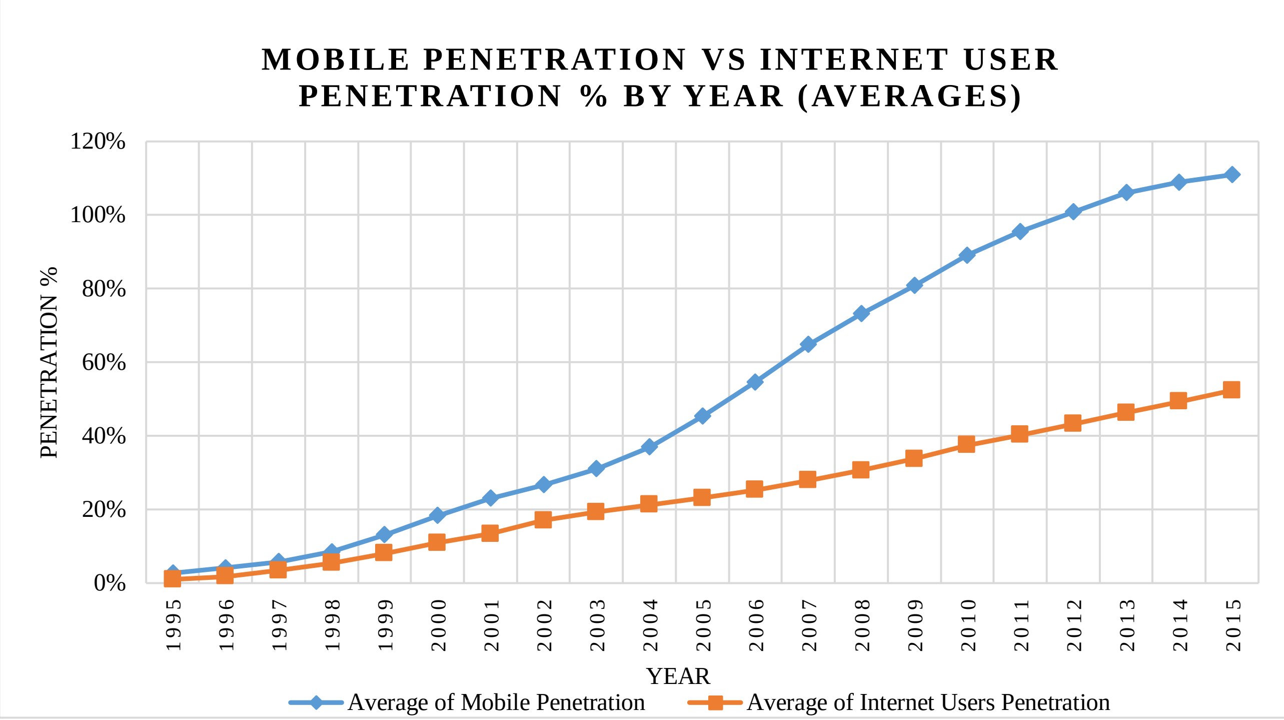

Figure 3.1.9. Mobile Penetration vs Internet User Penetration % by Year

From the initial findings in section 3.1. it can be expected that increasing: GDP per capita in current USD, urbanisation, and the working age population while decreasing unemployment rates and inflation rates will lead to increases in mobile and internet user penetration. It should be noted that the explanatory variables may only show statistically significant relationships with mobile and internet penetration between certain thresholds. With the graphical analysis of the data completed, the statistical analysis will be shown in the next section using the Stepwise OLS regression method and a Bayesian Lasso regression method as discussed in the research methodology.

3.2. Stepwise OLS Linear Regression Outputs

The variables were tested over the period 1995 up to and including 2015 for mobile and internet user penetration rates (target variables) for developing, developed and all countries. The variables were then tested using Stepwise OLS regression using the AIC score to decide which variables are kept in the model. The variables that were kept in the model are reflected in tables 3.2.1.1 and 3.2.1.2. This allowed the researcher to view the direction and degree of impact these variables have on the products and technologies being analysed.

3.2.1. Stepwise OLS Regression Findings

For table 3.2.1.1. all the variables are significant at the 10% statistically significant level and were percentage changes from the previous period. The numeric figures expressed by each explanatory variable in the model represents a one percentage change year on year for that variable leads to a x percentage change in the target variable e.g. a 1% change, 55% of the population to 55.55% of the population, in the population aged 15 to 64 leads to a 1.5% change, 60% to 60.90%, in mobile penetration.

3.2.1.1. Mobile Penetration 1995-2015

The target variable that was tested:

- Mobile Penetration

The explanatory variables that were inputted into the Stepwise OLS regression for analysis:

- GDP Per Capita in Current USD
- Age 0-14 % of Population
- Age 15-64 % of Population
- Age 65+ % of Population
- Exchange rate USD
- World GDP Growth Rate %
- Serious National Conflicts/Political Stability
- International Technology (Generational changes in underlying technology)
- Unemployment Rate %
- Regional GDP Growth Rate %
- Urban Population %
- Rural Population %

The explanatory variables that were kept in the Stepwise OLS regression model after the selection criteria, AIC score and significant at the 10% statistical significance level, was run.

The blank blocks in table 3.2.1.1 represent that the variable was not included in the model.

Mobile Penetration	**Developed Countries**	**Developing Countries**	**All Countries**
Variable	**1995-2015**	**1995-2015**	**1995-2015**
Intercept	0.5951	2.1307	1.3047
P-Value	0.0000	0.0000	0.0000
GDP Per Capita in current USD	-0.5881		
P-Value	0.0004		
Age 15-64 % of Population			28.4522
P-Value			0.0218
Age 0-14 % of Population	-3.9276		
P-Value	0.0281		
Exchange rate USD	-0.3047		
P-Value	0.0046		
World GDP Growth Rate %	2.6460		
P-Value	0.0053		
Rural population %			
P-Vale			
Urban Population %			
P-Value			
Unemployment Rate %		0.3696	0.3548
P-Value		0.0001	0.0000
Serious National Conflicts/Political Stability	0.0770		0.1249
P-Value	0.0021		0.0087
Age 65+ % of Population	3.7563		
P-Value	0.0028		
International Technology	-0.2204	-0.4952	-0.4004
P-Value	0.0000	0.0000	0.0000
Residual Standard Error	0.1989	1.5370	1.3250
Multiple R-squared	0.4689	0.0865	0.1056
Adjusted R-squared	0.4568	0.0830	0.1005
F-statistic	38.7200	24.7000	20.9200
P-Value	0.0000	0.0000	0.0000

Table 3.2.1.1. Mobile Penetration 1995-2015

Internet User Penetration 1995-2015

The target variable that was tested:

- Internet User Penetration

The explanatory variables that were inputted for the analysis:

- GDP Per Capita in Current USD
- Age 0-14 % of Population
- Age 15-64 % of Population
- Age 65+ % of Population
- Exchange rate USD

- World GDP Growth Rate %
- Serious National Conflicts/Political Stability
- International Technology
- Unemployment
- Regional GDP Growth Rate %
- Urban Population %
- Rural Population %

The explanatory variables that were kept in the Stepwise OLS regression model after the selection criteria, AIC score and significant at the 10% statistical significance level, was run

The blank blocks in table 3.2.1.2 represent that the variable was not included in the model.

Internet Users Per 100 People	**Developed Countries**	**Developing Countries**	**All Countries**
Variable	**1995-2015**	**1995-2015**	**1995-2015**
Intercept	1.3749	2.0868	1.7922
P-Value	0.0000	0.0000	0.0000
GDP Per Capita in current USD			
P-Value			
Age 15-64 % of Population		49.5325	39.8514
P-Value		0.0042	0.0007
Age 0-14 % of Population			
P-Value			
Exchange rate USD		0.4362	0.4262
P-Value		0.0302	0.0114
World GDP Growth Rate %			
P-Value			
Rural population %			
P-Vale			
Urban Population %			12.6752
P-Value			0.0254
Unemployment Rate %		1.0068	0.9888
P-Value		0.0000	0.0000
Serious National Conflicts/Political Stability			
P-Value			
Age 65+ % of Population	10.3435		
P-Value	0.0000		
International Technology	-0.3961	-0.5356	-0.479
P-Value	0.0000	0.0000	0.0000
Regional GDP Growth %	-1.5952		
P-Value	0.0176		
Residual Standard Error	0.3678	1.454	1.271
Multiple R-squared	0.3582	0.2805	0.2858
Adjusted R-squared	0.3520	0.2750	0.2808
F-statistic	57.87	50.68	56.67
P-Value	0.0000	0.0000	0.0000

Table 3.2.1.2 Internet User Penetration

The Stepwise OLS regression results show that having a higher percentage of the population older than 14 generally leads to increases in both mobile phone and internet user penetration. The age of the population has the highest changes to mobile and internet user penetration relative to the other statistically significant variables in the model. Changes in the generation of the underlying technology has a negative relationship across all the Stepwise OLS regression models. The negative relationship may be due to timing with the broader economy or may be down to the behaviour of switchers and leapfroggers as described by Jiang and Jain (2012). Unemployment rate shows a positive relationship for mobile and internet user penetration, but this may be due to factors such as low labour force participation rates and the methodology used to calculate the unemployment rate by a country. GDP growth does not have a very strong relationship with regards to mobile and internet user penetration. These models showed low R-squared figures, which mean they do not explain the variability of the response data around its mean. This may suggest that the original models expressed by Bass (1969), Bass and Norton (1987) and, Jiang and Jain (2012) may be correct for not adding economic variables in their models.

3.3. Bayesian Lasso Model Outputs

The results from using the Bayesian Lasso regression model used by Gelper and Stremersch (2014) for economic variable analysis with regards to technology adoption rates are discussed further below. As with the OLS Stepwise linear regression models, the variables were tested over the period 1995 to and including 2015 for mobile and internet user penetration rates (target variables) for developing, developed and all countries. The outputs of these models are in the tables 3.3.1.1 and 3.3.1.2. This allows the researcher to view the direction and degree of impact these variables have on the products and technologies being analysed.

The numeric figures expressed by each explanatory variable for the models in these tables represents a one percentage change year on year for that variable leads to a x percentage change in the target variable e.g. a 1% change, 55% of the population to 55.55% of the population, in the population aged 15 to 64 leads to a 1.5% change, 60% to 60.90%, in mobile penetration. Variables were selected by taking the median of the betas instead of mode for variable estimates. The amount of MCMC samples selected was 10 000.

3.3.1. Bayesian Lasso Model Findings

Mobile Penetration 1995-2015

The target variable that was tested:

- Mobile Penetration

The explanatory variables that were inputted for the analysis:

- GDP Per Capita in Current USD
- Age 0-14 % of Population
- Age 15-64 % of Population
- Age 65+ % of Population
- Exchange rate USD
- World GDP Growth Rate %
- Serious National Conflicts/Political Stability
- International Technology
- Unemployment
- Regional GDP Growth Rate %
- Urban Population %

- Rural Population %

The explanatory variables from the Bayesian Lasso regression models:

Mobile Penetration	**Developed Countries**	**Developing Countries**	**All Countries**
Variable	**1995-2015**	**1995-2015**	**1995-2015**
Intercept	0.6703	1.8980	1.2591
GDP Per Capita in current USD	-0.3407	0.0000	0.0000
Age 15-64 % of Population	0.0000	0.0000	3.7009
Exchange rate USD	-0.1500	0.1786	0.2248
World GDP Growth Rate %	1.8449	0.0000	0.0000
Serious National Conflicts/Political Stability	0.0619	0.0000	0.1328
Age 65+ % of Population	4.7097	0.0000	0.0000
International Technology	-0.2246	-0.4584	-0.3987
Age 0-14 % of Population	-1.9813	0.0000	0.0000
Unemployment Rate %	0.0000	0.1652	0.1930
Regional GDP Growth %	0.0000	0.0000	0.0000
Rural population % of population	0.0000	0.0000	0.0000
Urban population % of population	0.0000	0.0000	0.0000
Variance	0.0407	2.5452	1.9133
Lambda	0.1176	0.5892	0.2881
Eliminated Variable Count	5	9	7

Table 3.3.1.1 Mobile Penetration 1995-2015

Internet User Penetration 1995-2015

The target variable that was tested:

- Internet user Penetration

The explanatory variables that were inputted for the analysis:

- GDP Per Capita in Current USD
- Age 0-14 % of Population
- Age 15-64 % of Population
- Age 65+ % of Population
- Exchange rate USD
- World GDP Growth Rate %
- Serious National Conflicts/Political Stability
- International Technology
- Unemployment
- Regional GDP Growth Rate %
- Urban Population %
- Rural Population %

The explanatory variables that were kept in the Bayesian Lasso regression models:

Internet Users Per 100 People	**Developed Countries**	**Developing Countries**	**All Countries**
Variable	**1995-2015**	**1995-2015**	**1995-2015**
Intercept	1.2480	2.5330	1.9840
GDP Per Capita in current USD	0.0000	0.0000	0.0000
Age 15-64 % of Population	0.0000	0.0000	5.1514
Exchange rate USD	0.0000	0.0000	0.0000
World GDP Growth Rate %	0.0000	0.0000	0.0000
Serious National Conflicts/Political Stability	0.0000	0.0000	0.0739
Age 65+ % of Population	8.2192	0.0000	0.0000
International Technology	-0.3689	-0.6030	-0.5395
Age 0-14 % of Population	0.0000	0.0000	0.0000
Unemployment Rate %	0.0000	0.6116	0.6282
Regional GDP Growth %	-0.5896	0.0000	0.0000
Rural population % of population	0.0000	0.0000	0.0000
Urban population % of population	0.0000	0.0000	0.0000
Variance	0.1386	5.8249	4.3960
Lambda	0.1712	0.4742	0.3061
Eliminated Variable Count	9	10	8

Table 3.3.1.2 Internet User Penetration 1995-2015

The findings from the Bayesian Lasso models have similar findings to the Stepwise OLS models with the age of the population impacting adoption rates, as well as changes in the generation of the underlying technology used by mobile and internet users showing a negative relationship with both target variables. This may be due to the same reasons mentioned in the Stepwise OLS findings.

3.4. Variable Analysis

Each variable will be viewed and discussed based on the findings shown in the output tables from sections 3.2 and 3.3. Causes for the direction of the relationship between the explanatory and target variables will be theorised where possible.

3.4.1. GDP per capita in current USD

GDP per capita in current USD did not show a strong relationship with regards to mobile penetration or internet user penetration for both the Stepwise OLS and the Bayesian Lasso regression results. This does not agree with the research by Gelper and Stremersch (2014) where they found wealth to be a significant variable when modelling adoption rates. This may be due to GDP per capita only increasing the level of penetration initially to a certain threshold with the relationship then breaking down.

3.4.2. Population Ages 0 to 14 (% of Total)

Having an increase for the population in the youngest age range (ages 0-14) shows a negative relationship with mobile penetration for developed countries when viewing the results for both the Stepwise OLS and the Bayesian Lasso regression results. It was not shown to be significant in the other models.

3.4.3. Population Ages 15 to 64 (% of Total)

Having an increase in the population in the working age range of the population (ages 15-64) shows a positive relationship with both mobile and internet user penetration for both the Stepwise OLS and the Bayesian Lasso regression results when using all countries in the sample. This would be expected as this age range represents the working class of the population who will use new technologies for work and socialising.

3.4.4. Population Ages 65+ (% of Total)

Having an increase in the population in the retirement age range of the population (ages 65+) shows a positive relationship with both mobile and internet user penetration for developed countries for both the Stepwise OLS and the Bayesian Lasso regression results. This may be due to richer countries having a larger portion of their population in this age range as life expectancy may be longer than poorer countries.

3.4.3. Exchange Rate USD

A change in a countries exchange rate when compared to the United States Dollar has a negative relationship with mobile penetration for developed countries, but a positive relationship with mobile penetration and internet user penetration for developing countries when viewing the Stepwise OLS regression results. The Bayesian Lasso regression models show the same results as the Stepwise OLS regressions for mobile penetration, but do not show any significant relationship when modelling for internet user penetration.

3.4.4. Urban Population (% of Total)

A change in a country's percentage of the population living in urban areas has a positive relationship with internet user penetration for the Stepwise OLS regression model when using all the countries in the sample, but no significant relationship in the other models. This would be expected as the infrastructure for ICT services that provide internet connections can be expensive to build, which means that companies or governments may prefer to build it where a maximum number of the population can be reached, which would be in denser urban areas like cities.

3.4.3. Rural Population (% of Total)

Rural population as a percent of the population shows no significant relationship for all models.

3.4.4. Serious National Conflict/Political Instability

This variable was included by the researcher to minimise factors such as war or stock market crashes from the models outputs and therefore will not have its final relationships studied for the purpose of additions to the Bass Diffusion Model.

3.4.5. International Technology (Generational Changes)

When viewing the generational changes in mobile technology, the Stepwise OLS and Bayesian Lasso regression models all show that there is a negative relationship between the generational changes of the underlying technology with regards to mobile and internet user penetration. A cause of this relationship may be the timing of the technology changes as there was a launch of the improvement technology during the dot com crash of 2001 and the mobile internet usage started its major increases with smartphones from 2007 which happened during the financial crisis of 2007/2008. Another cause may be due to consumers waiting for technology to become cheaper before they adopt it, which would result in a lag after the initial launch.

3.4.6. Regional GDP Growth (%)

While not included in the Stepwise OLS regression outputs, the Bayesian Lasso regression models show that there is a negative relationship between the regional GDP growth percent with regards to internet user penetration for developed countries. This is probably due to country selection in the sample groups.

3.4.7. Unemployment Rate %

When viewing the unemployment rate %, the Stepwise OLS and Bayesian Lasso regression models both show that there is a positive relationship for both mobile and internet penetration rates for developing countries, but no significant relationship for developed countries. Unemployment rates by itself may not give the full picture of the labour force as variables such as wage levels, labour force participation rate and other broader definitions of unemployment would also need to be viewed.

3.4.8. World Growth Rate %

There is shown to be a positive relationship for developed countries when using the Stepwise OLS and Bayesian Lasso regression models for mobile penetration, but no significant relationship for any of the other models. The global growth rate indicates the general well-being of the global economy, therefore if it increases it should positively increase the rate of adoption for the mobile user and internet user penetration. This can be down to a multitude of factors such as there being an increase of new device sales, which leads to an increase in the cheaper second hand market, therefore making the devices with the technology cheaper to obtain. While this holds true for developed countries with regards to mobile penetration it does not hold true for internet user penetration for developed countries and not for developing countries with regards to both mobile and internet user penetration rates. This may suggest that changes to the levels of technology adoption for the global market is not significantly impacted by changes to the global economy.

3.5. Demographical, Technological and Economic Variable Linkages with Bass Diffusion Model

To tie the analysis together this section will summarise the findings of the three main components being demographical, technological and economic factors that were studied with regards to the adoption rates of a new technology or product for a country.

3.5.1. Demographical Factors

Previous research has shown that the characteristics of consumers in the potential market plays a significant role in the speed of technology adoption. These characteristics previously focused on the willingness of a consumer to take the risk of adopting a new technology being innovators and imitators, and their willingness to wait before adopting a technology being switchers and leapfroggers. This research added the age element to the adoption rate of a new technology or product and was shown to be significant in the adoption rate. The demographical factor of urbanisation was shown to play a role for improved rates of internet user adoption.

3.5.2. Generational Changes in Technology

Previous research by Norton and Bass (1987) and, Jiang and Jain (2012) introduced the generational changes in a technology or product as a factor in the rate of adoption. This research tested whether there is a relationship between generational changes in the underlying technology in the ICT sector and the adoption rates for mobile and internet users of a country. There was shown to be a significant relationship, but the relationship was shown to be negative. This may be related to the characteristics of adopters mentioned in 3.5.1 or it may be due to a lag effect for adoption of the new technology. The reasoning for this will require further specialised research on the topic which is beyond the scope of this work.

3.5.3. Economic Factors

Previous research showed that wealth played a role in the adoption rates of technology adoption as well as showing that consumers in the ICT sector are price sensitive, which held true when viewing the absolute levels of adoption i.e. developed countries have higher initial rates of adoption compared to developing countries, but it did not play a significant role when viewing year on year changes to technology adoption in the ICT sector when using macro-economic factors. This may be due to the good over time having a low cost to entry, therefore once that threshold to entry is reached the consumer will buy it regardless of whether they become wealthier or stay the same.

Conclusion

The telecommunications industry has grown at a rapid rate from the period of the 1980s to 2018. The growth of the industry has led to subscriber bases reaching up to 250 million subscriptions in a country per mobile operator, although this is an outlier. This paper reviewed the relationship of ICT services (mobile and internet services) with various demographical, technological and economic factors that have previously been shown to impact the rate of adoption for other technologies in the past. The methods used to test these relationships were the Stepwise OLS and Bayesian Lasso regression techniques over the period 1995 up to and including 2015. The age of the population and change in technology generation were shown to be significant in predicting the change of adoption rates for mobile penetration and internet user penetration. The development status of a country i.e. developed or developing was also tested and found that developed countries have higher adoption rates for ICT services than its developing country peers. The pattern of the adoption rates when viewing all countries in the sample showed an S-shape curve which agrees with the previous theory on the rate of adoption for a new technology or product. This gives reason to believe that the Bass Diffusion Model is applicable to mobile and internet penetration levels if the average penetration globally is used.

The second part of this work focused on the digital divide globally with developed countries having high levels of access to information through higher internet penetration rates while poorer countries tend to have low internet penetration rates which will impact the population's access to information and therefore, negatively impact productivity. This can be caused by high cost to entry i.e. price of laptops or mobile phones for products that are needed to run the technology. This will link in with studies that showed that subscribers in developing countries are price elastic. While increasing internet and mobile penetration has been shown to increase economic factors such as trade and globalisation, the importance of investment in ICT services, there are however certain factions who believe that the investment funds in telecommunication services should rather be used for other sectors such as healthcare and education. A sub section of the "Second-Level Digital Divide" is on the use of the provided ICT services where people in countries with high access of mobile and internet facilities may not know how to use them properly due to a lack of skills. This "Second-Level Digital Divide" may be more prominent in developing countries as large portions of their population will only gain access to the internet 15 years after those in developed countries and early adopters within the developing countries meaning their skill levels with regards to the use of the internet and related technologies may be well below average. If GDP per capita is raised by improved ICT services in poorer countries this could benefit richer countries by increasing global demand for goods and services, therefore providing an incentive for richer nations to help poorer countries gain access to internet services, but with its current trajectory there may need to be large sums of investment in infrastructure as well as general education on how to use the internet to achieve this.

Follow up studies should firstly, look into the economic impact that the first and second level digital divides have caused over an extended period on not only the population that were late adopters, but also on the burden this places on early adopters in having to educate and provide aid to the late adopters in the future. Secondly, testing and then explaining why a technological generation change for a technology can lead to decreases in the adoption rate of a new product or technology and whether the negative relationship applies to other technologies or products or was a function of other market factors. Lastly, viewing the broader employment climate of a country and testing whether the other employment metrics impact the adoption rates for a new technology or product. This will give an in-depth version of the Bass Diffusion Model as the current version may still be too high level.

Appendix

Table 1. Mobile penetration rates by region

Average of Mobile Penetration									
Year	**Africa**	**Asia**	**Australasia**	**Central America**	**Eastern Europe**	**Middle East**	**North America**	**South America**	**Western Europe**
1995	0%	2%	11%	1%	3%	1%	11%	1%	8%
1996	0%	4%	18%	1%	4%	1%	14%	1%	12%
1997	0%	6%	20%	2%	5%	2%	17%	3%	18%
1998	1%	8%	24%	3%	7%	3%	21%	5%	28%
1999	1%	12%	35%	6%	10%	4%	27%	9%	46%
2000	3%	15%	42%	9%	13%	6%	33%	13%	66%
2001	5%	18%	58%	14%	19%	9%	40%	17%	76%
2002	6%	22%	63%	18%	25%	14%	43%	20%	81%
2003	8%	25%	68%	23%	33%	20%	48%	24%	87%
2004	11%	30%	78%	28%	44%	26%	55%	34%	92%
2005	15%	37%	88%	34%	61%	36%	61%	49%	99%
2006	22%	45%	93%	41%	81%	46%	67%	61%	106%
2007	30%	57%	100%	46%	95%	62%	72%	72%	113%
2008	40%	68%	105%	54%	98%	73%	76%	85%	117%
2009	47%	76%	105%	57%	110%	90%	80%	94%	118%
2010	59%	88%	104%	72%	120%	95%	83%	105%	117%
2011	68%	100%	107%	83%	118%	99%	86%	115%	119%
2012	74%	108%	108%	98%	123%	100%	88%	122%	120%
2013	81%	113%	106%	117%	127%	106%	89%	127%	121%
2014	87%	116%	122%	113%	128%	107%	96%	126%	121%
2015	90%	120%	127%	118%	129%	111%	100%	122%	119%

Table 2. Internet user penetration per region

Average of Internet Users Penetration									
Year	**Africa**	**Asia**	**Australasia**	**Central America**	**Eastern Europe**	**Middle East**	**North America**	**South America**	**Western Europe**
1995	0,04%	0,28%	3,82%	0,26%	0,76%	0,04%	6,70%	0,16%	3,43%
1996	0,06%	0,70%	5,66%	0,52%	1,39%	0,19%	11,59%	0,36%	6,22%
1997	0,12%	1,50%	15,49%	1,13%	3,39%	0,64%	18,34%	0,62%	10,80%
1998	0,23%	2,45%	31,22%	1,97%	5,15%	0,76%	27,50%	1,14%	15,30%
1999	0,39%	5,49%	41,14%	2,88%	6,57%	1,01%	36,02%	2,42%	23,50%
2000	0,65%	9,17%	47,07%	5,44%	7,82%	1,64%	47,19%	6,03%	31,46%
2001	0,85%	11,94%	52,97%	8,30%	9,58%	2,54%	54,64%	7,68%	38,17%
2002	1,08%	14,29%	58,46%	15,90%	14,45%	4,67%	60,19%	9,97%	49,66%
2003	1,42%	15,63%	60,15%	16,62%	17,49%	7,53%	62,95%	12,30%	56,53%
2004	2,18%	18,39%	61,46%	17,45%	20,89%	8,57%	65,36%	15,37%	59,51%
2005	2,63%	20,13%	62,86%	19,64%	23,68%	10,48%	69,81%	17,23%	62,94%
2006	3,58%	22,03%	67,50%	22,31%	26,37%	13,43%	70,67%	21,03%	65,50%
2007	4,19%	24,36%	69,61%	24,61%	28,86%	17,97%	74,10%	25,01%	70,87%
2008	6,29%	26,68%	71,85%	27,00%	33,31%	21,63%	75,35%	27,47%	74,00%
2009	7,74%	29,93%	76,98%	30,34%	39,68%	25,15%	75,65%	32,32%	76,47%
2010	10,13%	35,37%	78,23%	33,78%	45,04%	30,12%	76,00%	37,91%	79,31%
2011	12,10%	39,14%	80,36%	38,19%	49,14%	32,60%	76,36%	43,86%	80,00%
2012	14,42%	41,33%	80,50%	43,63%	54,94%	35,16%	78,85%	48,75%	81,62%
2013	16,50%	46,71%	83,12%	44,71%	58,70%	41,57%	78,60%	51,53%	83,00%
2014	19,32%	50,31%	84,75%	48,70%	62,96%	46,13%	80,06%	53,51%	85,20%
2015	22,27%	53,90%	86,39%	58,60%	65,10%	48,96%	81,51%	58,75%	86,44%

Table 3. 59 country sample

Afghanistan	Kazakhstan
Albania	Kenya
Argentina	Madagascar
Armenia	Mali
Azerbaijan	Mexico
Bangladesh	Morocco
Belarus	Mozambique
Bolivia	New Zealand
Botswana	Nigeria
Brazil	Norway
Cameroon	Poland
Canada	Qatar
Central African Republic	Romania
Chad	Russia
Chile	Rwanda
China	Republic of Congo
Colombia	Saudi Arabia
Costa Rica	South Africa
DRC	South Korea
Dominican Republic	Spain
France	Swaziland
Germany	Sweden
Ghana	Switzerland
Iceland	Syria
India	Tanzania
Iran	Thailand
Indonesia	Uganda
Italy	Ukraine
Ivory Coast	United Kingdom
Japan	USA

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