Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
Differentiating mobile broadband policies across diffusion stages: A panel data analysis

Mekuria Haile Teklemariam, Youngsun Kwon *

School of Business and Technology Management, College of Business, KAIST, South Korea

ARTICLE INFO

Keywords:
Digital divide
Mobile broadband
Diffusion
Adoption
Policy mix
Panel data

ABSTRACT

This paper finds that policy mixes for mobile broadband diffusion need to be differentiated depending on where a country is situated in three stages of mobile broadband diffusion because as a mobile broadband market grows, demand constraints hindering subscription of mobile broadband will also change. A total of 115 countries are clustered into three groups (Take-off, Fast-Diffusion, and Saturated), categorized by their diffusion rates and diffusion speeds over four years from 2013 to 2016. With pooled and fixed effect panel data models, this paper examines which variables out of 23 explanatory variables were effective in promoting mobile broadband adoption globally. Further, by interacting explanatory variables with two group dummies, this paper identifies differential slope (policy) effects of each explanatory variable on mobile broadband adoption. The paper concludes that, among the three groups, considerable gaps exist in the size of effective policy choice sets: six for Take-off, ten for Fast-diffusion, and thirteen for Saturated, suggesting that the countries in the Take-off stage have a very narrow degree of latitude for developing mobile broadband promotion strategies.

1. Introduction

We live in the early stage of the 4th industrial revolution, in which information communication technologies (ICTs) weave our society together more densely than ever before. The latest technological devices, such as desktop computers, tablets, smart phones and other smart devices, are mostly used in connection with the broadband infrastructure, enabling them to communicate in real time among themselves and the people using them. As mobility and ubiquitous connections have become essential in daily life in all nations, the presence and use of mobile broadband internet tend to be a critical economic and social indicator, representing the global competitiveness of nations (Heshmati; Rashidghalam, 2016; Mayer, Madden, & Wu, 2020).

The rate of global internet uptake has increased consistently with the rapid growth of the mobile broadband subscription and the gradual growth of fixed broadband subscription. According to the International Telecommunications Union (ITU, 2018) estimation, the global status of broadband use was 51.2 percent of the world population in 2018. Mobile broadband subscription rates vary with income level: on average, that rate is 80 percent of the population in developed countries, 45 percent in developing countries, and only 20 percent in the least developed countries, indicating that even though globally internet connections have grown significantly,
a considerable level of digital divide among countries remains.

Countries have tried to provide inclusive and sustainable broadband services for their citizens, but not many of them have been able to reach these goals due to their differential capabilities in governing the mobile broadband ecosystem with balanced strategies between the demand and supply sides of the services (Silva, Badasyan, & Busby, 2018; Katz & Callorda, 2018). The exclusion of citizens from the services can also be measured by the demand gap, setting aside the supply gap due to the absence of accessible broadband networks, because more supply does not necessarily entail more demand (Hargittai & Walejko, 2008). The demand gap becomes wider if supply increases more rapidly than demand, and demand gaps throughout the world are still commonly observed. This gap is around 20 percent on average in high adopter countries, suggesting that digital exclusion due to demand shortage is still an important policy issue even in these economies. In contrast, the gap in laggard adopter countries is roughly quadruple that of the high adopter countries, implying that digital exclusion due to weak demand is both a serious economic problem and, of even more concern, has not significantly shrunk over time counter to the predictions of Vicente and Lopez (2011).

At a given time point, reducing the demand gap requires increasing mobile broadband subscription without regard to the level of the mobile broadband supply gap. In addition, government policies for enhancing broadband subscription need to vary with the broadband adoption (diffusion) level because as the mobile broadband market matures, demand constraints hindering subscription to mobile broadband will also change. As an example, in an early stage of mobile broadband adoption, offering affordable devices is likely to be more effective than making more content or applications available to users because internet content or applications are useless for users without devices. Although the argument (hypothesis) that mobile broadband policies need to be differentiated across countries is not new, there have been no empirical studies rigorously testing it. In order to test various hypotheses about differential effects of broadband policies along the dimension of mobile broadband diffusion and speed, a panel dataset collected across countries over time is essential. This research study collects a panel dataset for 115 countries for the four years from 2013 to 2016 in order to analyze differential effects of government policies on mobile broadband adoption.

This study first focuses on identifying the significant factors of broadband adoption rate globally by using panel data regression models. By comparing the outcomes of a pooled panel data model with those of a fixed effect panel data model, we show that, as is often the case (Green, 1997), the fixed effect model performs better than the pooled model in explaining the effects of factors on mobile broadband adoption and, further, that countries at different stages of mobile broadband diffusion have indeed different intercepts, indicating that the 115 countries belong to different population groups (Rogers, 1995). Secondly, this paper utilizes interaction terms, interacting each explanatory variable with group dummies, in order to figure out differential slope effects of government policies on mobile broadband adoption. These analyses allow us to understand which variables are more effective than others across different stages of broadband diffusion. In order to attain these goals, we classified all sample countries into three groups—Take-off, Fast-diffusion, and Saturated—by utilizing the average mobile broadband diffusion rates and the growth (speed) of mobile broadband diffusion for the four years.

To sum up, this paper finds that considerable gaps exist among the three groups with respect to the size of effective policy choice sets: six for Take-off, ten for Fast-diffusion, and thirteen for Saturated (Table 6). This implies that Take-off group countries, mostly underdeveloped countries, have the least degree of latitude in developing mobile broadband promotion policies, whereas Saturated group countries have the largest set of policy choices. It is also found that those in a Take-off group who strive to ladder up to the Fast-diffusion stage should direct their efforts towards economic development, education, computer and electricity supply, and online content supply, while increasing competition in their mobile broadband markets and facilitating investments in fixed and mobile broadband networks. Furthermore, content diversity and availability become influential when a country moves from the Fast-diffusion to Saturated stage.

The structure of this paper is as follows. Section 2 briefly reviews previous studies on the determinants of broadband diffusion and discusses the new contributions of this research. Section 3 introduces the research methodology, including research questions, models and data. Section 4 presents the results of analyses, and their policy implications are discussed in section 5. Section 6 concludes the paper, emphasizing its key contributions.

2. Literature review on determinants of broadband adoption

Empirical research is often confined by sample size and data availability, and becomes even more difficult when it is about policy research, mostly capitalizing on annual data. A small sample size limits the number of independent variables in research due to the need to keep the degrees of freedom at an appropriate level, even when more data for explanatory variables are available to researchers. This research, as noted in the introduction, utilizes a panel dataset, enabling us to add more independent variables to research models than previous studies. This paper uses not only the explanatory variables used in the previous literature, but also draws on six more variables that may contribute to explaining the adoption behaviors of mobile broadband users. This section reviews the models and variables of previous research, discusses the hypothetical roles of the newly added explanatory variables in understanding mobile broadband adoption behavior, and briefly summarizes new contributions of this research.

---

2 Demand gap is defined by the coverage minus subscription rates, and coverage is measured by the ratio of population living in areas where mobile broadband services are accessible. Supply gap (or shortage) is measured by 100 percent minus the coverage.
well, utilizing a panel dataset but focusing on the network externality effect on fixed broadband adoption. According to Andres et al. (2010), the effects of broadband adoption determinants with worldwide cross-country data. This paper reviewed previous studies, especially differences at times. Even though there have been many studies on broadband adoption decision making and policy, only a few studied those using panel datasets, on mobile broadband adoption and in order to effectively present an extensive literature review, this tistically significant positive effect on fixed broadband adoption even though the sign of telephone-lines was negative for high-income nations.

 subsection first identifies economic explanatory variables, derived from demand and supply theories, and then social ones.

### 2.1. Determinants of broadband adoption used in the previous literature

Many studies about internet uptake and diffusion have been conducted by scholars. Their findings are often similar, but have minor differences at times. Even though there have been many studies on broadband adoption decision making and policy, only a few studied the effects of broadband adoption determinants with worldwide cross-country data. This paper reviewed previous studies, especially those using panel datasets, on mobile broadband adoption and in order to effectively present an extensive literature review, this subsection first identifies economic explanatory variables, derived from demand and supply theories, and then social ones.

Andres, Cuberes, Diouf, and Serebrisky (2010) is one of the early studies on broadband diffusion that considered mobile broadband as well, utilizing a panel dataset but focusing on the network externality effect on fixed broadband adoption. According to Andres et al. (2010), GDP per capita income, telephone-lines, mobile subscription, and number of computers per person turned out to have a statistically significant positive effect on fixed broadband adoption even though the sign of telephone-lines was negative for high-income nations. Utilizing OECD mobile broadband panel data from 2003 to 2008, Lee, Marcu, and Lee (2011) found that population density, fixed broadband price, and the availability of multiple standardization of the mobile broadband service delivery policies were statistically significant determinants of mobile broadband adoption. Kyrriakidou, Michalakelis, and Spicopoulos (2013), studying broadband diffusion with an OECD dataset, found that e-government online availability, computer ownership per capita, productive age and population density have statistically significant effects on broadband penetration. García-Murillo (2005), focusing on the effect of unbundling policy, found that gross national income (GNI) per capita and the total population of the countries have positive effects on broadband diffusion. Baigorri and Maldonado (2018), drawing on Brazilian regional data, showed that the price of mobile broadband services is an important factor, and both Na, Hwang, and Kim (2018) and Viard and Economides (2014) indicated that online services which are complementary to broadband connection service are positively correlated with broadband diffusion. Garcia-Murillo (2005), focusing on the effect of unbundling policy, found that gross national income (GNI) per capita and the total population of the countries have positive effects on broadband diffusion. Lin and Wu (2013) also identified content as an important factor, and both Na, Hwang, and Kim (2018) and Viard and Economides (2014) indicated that online services which are complementary to broadband connection service are positively correlated with broadband diffusion. Lin and Wu (2013) also identified content as an important factor of broadband adoption. Viard and Economides (2014) found that urbanization and a late productive age (40–64) played a positive role in broadband adoption determinants. Silva et al. (2018) shows that as urban areas have more consumers who are well-educated and rich than rural areas, urbanization ratios are positively correlated with mobile broadband adoption rates. Electricity consumption per capita was also identified by Armey and Hosman (2016) as one of the determinants of broadband adoption, and Rohman and Bohlin (2012), relying on the OECD member states data from 2008 to 2010, showed that doubling the internet download speed contributes to a 0.3 percent increase in broadband connections, also confirmed by Xu, Forman, and Hu (2018).

Competition in network service industries has been identified as an important factor for promoting broadband diffusion by many previous studies, such as Lee et al. (2011), Ovington, Smith, Santamaría, and Stammati (2017), Lin and Wu (2013), and Yates, Gulati, and Marabelli (2015). With respect to competition, unbundling local loops was found to improve broadband adoption in both urban and sub-urban areas (Fuchs, 2009). Cincera, Dewulf, and Estache (2012), and Ovington et al. (2017) showed that service-based and

### Table 1

| Category                              | Explanatory variables [Dependent variable: Broadband adoption/diffusion] | Expected signs |
|---------------------------------------|------------------------------------------------------------------------|----------------|
| Demand-side (10)                      | GNI Per capita income                                                 | Positive       |
|                                       | Number of computers per person (Complementary)                        | Positive       |
|                                       | Fixed broadband subscription (Complementary/Substitute)                | Positive/Negative |
|                                       | Mobile broadband price per minute                                     | Negative       |
|                                       | Fixed broadband price (Complementary/Substitute)                      | Negative/Positive |
|                                       | Productive age (15–64) population                                    | Positive       |
|                                       | Content online services (Complementary)                               | Positive       |
|                                       | Electricity consumption per capita (Complementary)                    | Positive       |
|                                       | Internet download speed quality of services                           | Positive       |
|                                       | Education level (Skill)                                               | Positive       |
|                                       | Population density (A proxy for network rollout cost)                 | Positive       |
|                                       | Urbanization (A proxy for network rollout cost)                       | Positive       |
| Supply-side (2)                       |                                                                         |                |
|                                       |                                                                         |                |
| Government policy variables (11)      | Competition level (Herfindahl-Hirschman Index, Supply-side)           | Negative       |
|                                       | Service-based competition (Supply-side)                               | Positive       |
|                                       | ICT laws and policy availability (Demand-side)                        | Positive       |
|                                       | Corruption management quality (Supply-side)                           | Positive       |
|                                       | Device tax level (Demand-side)                                        | Negative       |
|                                       | Female labor participation rate (Demand-side)                         | Positive       |
|                                       | Applications availability in the first language (Demand-side)         | Positive       |
|                                       | Lag software piracy rate (Demand-side)                                | Negative/Positive |
|                                       | Government broadband promotion (Demand-side)                          | Positive       |
|                                       | Mobile broadband coverage (Quantity supplied)                         | Positive       |
|                                       | Spectrum allocation per operator (Demand-side)                        | Positive       |
|                                       |                                                                         |                |

---

a Mobile networks that provide download speeds of at least 256 kbps (ITU).

b In parenthesis, complementary means complementary to broadband services, and demand and supply-side in policy variables mean that the policy variables influence either one of the two sides.

3 It was, as expected, positive for low-income nations.
facility-based competitions have a positive and significant effect on internet connections. These findings related to competition are similar to those of Calzada and Martínez (2013). However, there are also contradictory findings that showed negative effects of service-based competition on broadband internet connections (Bouckaert, van Dijk, & Verboven, 2010; Crandall, Eisenach, & Ingraham, 2013; Höffler, 2007).

Previous studies of broadband adoption also include studies using world data, including those of developing countries. Yates, Girish, and Weiss (2013) and Yates et al. (2015) used 121 and 103 country cross-section data, respectively, for different years in analyzing mobile broadband diffusion. These two studies by Yates, Gulati, and Weiss (2013; 2015) reported that platform competition index, regulatory quality, GNI per capita, law effectiveness, and the extent of corruption management are positively associated with broadband diffusion. Another feature of the studies by Yates et al. (2013; 2015) is that they included socio-institutional variables such as law effectiveness and corruption management in their analyses. Bertschek, Briglauer, Hüschelrath, Kauf, and Niebel (2016), a survey study, identified the positive impacts of mobile broadband on productivity, economic growth, and regional development and emphasized the importance of coordinated implementation of broadband inclusion policies by the government in enhancing mobile broadband diffusion. Lin and Wu (2013), using OECD data, found that education played a positive role in broadband adoption, and Gulati and Yates (2012) reported that the regulatory quality was marginally statistically significant (at a ten percent level of significance) in explaining mobile broadband adoption. Grubesic (2012) and Hill, Troshani, and Burgan (2014) indicated that network deployment, low population density, unavailability of comprehensive law, and profitability of companies in urban areas make rural connections challenging and difficult.

Table 1 summarizes the explanatory variables used in the previous studies and presents the expected signs of the coefficients. Based on microeconomics theories, the explanatory variables are classified into three groups: demand-side variables affecting users’ demand for mobile broadband services, supply-side variables affecting the costs of providing mobile broadband services, and social or regulatory factors influencing users’ demand and service providers’ supply decision-making behaviors.

2.2. Newly considered explanatory variables of broadband adoption

This study considers six additional variables, likely to be correlated with mobile broadband adoption according to economic theories, but not used in previous empirical studies. This expansion is possible because we collected a sufficiently large amount of data to run regression models with additional variables. The added six variables include the female labor participation ratio, the application availability in the first language, software piracy rate, broadband promotion performance, mobile broadband coverage level, and spectrum allocation per operator. Apart from software piracy rates, the other five variables are assumed to be positively correlated with demand for mobile broadband adoption.

2.2.1. Female labor participation ratio

Bianchi, Mikie, Sayer, and Robinson (2000) show that most of the housekeeping and child-care responsibilities are undertaken by females in the US even when married couples are both employed. Hence, it could be noted that there is less participation of females relative to males in the labor market. Efobi, Tanankem, and Asongu (2018) found that improving women’s access to communication technologies increases their labor market participation and, in turn, enhances women’s incentives to subscribe to mobile broadband services. In addition, female spouses are found to play a leading role in household broadband subscription decisions (Choudrie & Lee, 2004; Dwivedi; Lal, 2007) and female labor participation increases household income. Hence, it can be hypothesized that the more women participate in labor opportunities in a nation, the more mobile broadband uptake there is in that nation.

2.2.2. Applications in the first language

Na et al. (2018) noted that when consumers were required to use broadband applications of a language different from their own first language, it became an obstacle that reduced the use of the online services and content. Viard and Economides (2014) identified linguistic isolation as one of the serious impediments for broadband adoption, and suggested that creating digital content and applications in the first language might reduce this isolation (See also Dimaggio, Hargittai, Celeste, & Shafer, 2004). Wunnava and Leiter (2009) also found English-language proficiency to be one of the positive and significant contributors to the diffusion of mobile broadband services. Having not found any research, however, that tests the impact of the software applications available in the first language on the mobile broadband subscription rate, we developed a testable hypothesis that the more content and applications in the first language are offered, the more likely it is to increase broadband adoption in a nation.

2.2.3. Software piracy rate

Goel and Nelson (2009) studied the effects of internet and computer users on piracy and found that the greater the number of internet users, the lower the piracy rate of software. Similarly, Boyce (2011) found that broadband penetration rate improvement would reduce software piracy and Martinez-Sanchez and Romeu (2018) showed that a one percentage point increase in the ratio of fixed broadband uptake to population would decrease the software piracy rate by 0.07 percentage points. These scholars presumed that the more broadband connections there are, the less software piracy there would be. However, there could be a reverse relationship between software piracy and mobile broadband subscription rate because well-established piracy protection regulation can increase the supply of content and useful applications, eventually leading to increased mobile broadband subscription. Therefore, we set up a hypothesis that the lower the software piracy rate is, the higher the rate of mobile broadband adoption will be. To mitigate the endogeneity issue between the mobile broadband adoption rate and software piracy rate, the software piracy variable lagged by one year was used in our analysis.
2.2.4. Government broadband promotion performance level

Broadband promotion by the government refers to the communication efforts used to inform or persuade the citizens of the merits of broadband internet uptake and usage. The aim of promotion is to increase awareness, create interest for usage, and then induce subscriptions. It has been considered one of the basic elements of the broadband inclusion determinants in addition to the government regulatory role. Goss (1979) noted that previous studies often focused on individual skill and financial capabilities, rather than on behavioral indicators that might influence individual decisions about broadband subscriptions. This paper assumes that the governments’ efforts to promote broadband adoption by persuading citizens would facilitate mobile broadband adoption.

2.2.5. Mobile broadband coverage

Mobile broadband coverage, measured by the percentage of the population who can get access to mobile broadband networks in a nation, is a supply constraint that limits mobile broadband adoption. Accordingly, the mobile broadband adoption rate cannot exceed the mobile broadband coverage. Dobson, Jackson, and Gengatharen (2013) and Prieger (2013) reported that, even in developed economies, there were coverage (supply) gaps, defined as differences between 100 percent minus coverages, between urban and rural areas as more operators focused on urban areas due to low rollout cost and high profit potential. Therefore, it is hypothesized that the national mobile broadband subscription rate will increase as mobile broadband coverage expands.

2.2.6. Spectrum per operator

Spectrum is an essential input in the provision of mobile communications and internet services (Kwon & Kim, 2012; Kwon, Lee, & Oh, 2010; Kwon, Park, & Rhee, 2017). Many scholars have argued against the command and control approach of governments to spectrum management (Kwon & Kim, 2012; Kwon et al., 2010). Others also suggested that market-friendly spectrum management policies allowing trading, leasing, and sharing would enable the better use of scarce spectrum resources (Beard, Ford, Spiwak, & Stern, 2011; Bykowsky, 2003; Kwon & Kim, 2012). Spectrum is an indispensable resource for mobile broadband service delivery because the speed of connection largely depends on bandwidth (Lundborg, Reichl, & Ruhle, 2012; Kwon et al., 2017). Therefore, this study hypothesizes that spectrum per operator in MHz is positively correlated with mobile broadband adoption.

2.3. Contributions of this study

In previous broadband adoption studies, there were cross-section analyses, with only one-year data, of fixed and mobile broadband adoption using data from more than one hundred countries (Billon, Marco, & Lera-Lopez, 2009; Gulati & Yates, 2012; Yates et al., 2013; 2015) and there were also panel data analyses with only OECD countries or state level data in a country (Distaso, Lupi, & Manenti, 2006; Kiiński & Pohjola, 2002; Lee et al., 2011; Lin & Wu, 2013). Andres et al. (2010) is the only exception that used panel data analysis with a worldwide dataset for 214 countries over 15 years from 1990 to 2004, but this study focuses on fixed broadband diffusion, using only five explanatory variables to explain broadband adoption.\(^4\) The small number of explanatory variables is not surprising because not many explanatory variables, measured consistently across many countries, were available, especially in the past.

For the past ten years or so, international telecommunications environments have changed drastically from fixed broadband to mobile broadband as mobile telecommunication services evolved from 2G to 3G and 4G services (Jung & Kwon, 2015; Nam, Kwon, Kim, & Lee, 2009). During this transition period, smartphones and smart devices emerged as key platforms of telecommunication. In addition, UN and ITU accumulated various data across countries, which enriched researchers’ choice of explanatory variables. Therefore, this paper, as stated in the introduction, collected data of 115 countries for four years from 2013 to 2016 in order to identify determinants of mobile broadband adoption in smartphone environments and analyze which determinants are more effective than others along mobile broadband diffusion stages in boosting mobile broadband adoption.\(^5\) This exploration of efficacy is the key contribution of this research in understanding mobile broadband adoption.

3. Research hypothesis, data and models

3.1. Research hypotheses

This paper has two sets of hypotheses: one set to test the effects of explanatory variables, both those used in previous studies and those newly added, on mobile broadband diffusion rate across countries, and the other set to test the differential effects of policy variables on mobile broadband adoption rate across the different stages of mobile broadband adoption. The first set of hypotheses, summarized in Table 1, aims to both reconfirm whether the signs of determinants of mobile broadband adoption are congruent with those of previous fixed and mobile broadband adoption studies and to estimate the effects of newly added variables on mobile broadband adoption. Another main contribution of this study is to estimate the differential effects of policy variables on mobile broadband adoptions across the mobile broadband diffusion stages. In order to attain this goal, this paper interacts the variables, such as control of software piracy, computer use, download speed, applications in the first language, broadband promotion, facility-based competition, and mobile broadband coverage, with the group dummies for diffusion stages.

---

\(^4\) The five explanatory variables are real GDP per capita, real cost, lines per capita, computers per capita, and Internet users (p. 330).

\(^5\) This is the largest dataset we can currently construct because there is a tradeoff between sample countries and years.
6 Because, while clustering the 117 countries into three groups, we found that these two countries recorded exceptionally high growth 
6 GSMA: https://www.mobileconnectivityindex.com (13) from WITS: https://wits.worldbank.org.
3 Data sources: (1), (12) and (18) from World Bank https://data.worldbank.org/indicator. (2), (3), (8), (10), (14), (15), (20), and (21) from WEF: http://reports.weforum.org/global-information-technology-report-2016 (4) And (5) from ITU: https://www.itu.int/en/ITU-D/Statistics (6) And (11) from IMF: https://data.imf.org (7), and (16) from World Bank: https://info.worldbank.org/governance/wgi (9), (17), (19), (22), and (23) from GSMA: https://www.mobileconnectivityindex.com (13) from WITS: https://wits.worldbank.org.
3 These three clusters belong to each group. Appendix 2 also presents all sample countries in alphabetical order with their three key variable data.
Average MBB diffusion, MBB diffusion speed, and average GNI per capita.

Descriptive statistics of 26 explanatory variables are summarized in Appendix 3 and those of three clusters are presented in Table 3. From Fig. 1, Table 3 and Appendix 3, we can notice a few characteristics of the clustering. As expected from the S-shape innovation curve, the average values of the MBB diffusion level for Take-off, Fast-diffusion and Saturated were 11.1%, 41.7%, and 94.5%, respectively, while those of their MBB diffusion speed were 13.1%p, 36.6%p, and 22.9%p. These figures show that both the average MBB diffusion level and the average speed of MBB diffusion were low for the Take-off group, whereas the Fast-diffusion group recorded the rapidest diffusion speed and the Saturated group the highest diffusion level. The average GNI per capita values for the three groups—Take off, Fast-diffusion, and Saturated—were, respectively, $4.2 thousand, $17.8 thousand, and $51.8 thousand, implying that the three clusters are, on average, closely correlated with GNI per capita.

3.3. Research models

To capture the statistically significant determinants of mobile broadband adoption across countries over the four years, we first applied a pooled panel regression model, shown in Eq. (1), to the dynamic panel dataset that we introduced in the subsection above. The pooled model assumes that all countries included in the analysis are random samples from the same population and ignores differences among countries or clusters. In other words, the pooled model implies that all variables have the same effects on mobile broadband adoption across the countries. However, this is likely to be an implausible assumption because if the adoption pattern of mobile broadband follows the S-shape innovation curve, the effects of explanatory variables on mobile broadband adoption could vary along the innovation curve. Furthermore, the clustering analysis identified three different sub-groups, showing that the three groups within the sample countries are likely to come from three different population groups. Two well-known regression models that we can use to capture heterogeneity among these three groups are the fixed effect model and the fixed effect model with interaction terms. This paper first applied a least square dummy variable (LSDV) fixed effect model, shown in Eq. (2) to the same dataset, in order to capture heterogeneity existing among three groups. The LSDV fixed effect model assumes that the differences among the three groups
exist only in differential intercepts and there is no heterogeneity among the three groups in the effects (slopes) of explanatory variables on mobile broadband adoption. In order to extract differential slope effects among the three groups, this paper then added two interaction terms, \( x_i \beta_{24} + x_i \beta_{25} \), to the LSDV fixed effect model, as shown in Eq. (3). Computer availability, for example, could be an important factor affecting mobile broadband adoption at the Take-off and Fast-diffusion stages, but might not be one at the Saturated stage. From the coefficients of interaction terms, \( \beta_{24} \) and \( \beta_{25} \), we can separate out the differential effects of computer supply on mobile broadband diffusion.

### Table 4
Regression results of pooled and fixed effect models.

| Explanatory variables | Pooled model | Fixed effect model |
|-----------------------|--------------|--------------------|
|                       | Coefficients | t-value (p-value)  |
|                       | Coefficients | t-value (p-value)  |
| \([\text{Demand-side}]\) |              |                    |
| Intercept             | -48.517      | -2.163 (0.031)    |
| PCapinc               | 0.066        | 1.016 (0.310)    |
| Compu                 | 0.372        | 5.901 (0.000)    |
| Fixbub               | -0.602       | -1.925 (0.055)   |
| Pmobb                | -0.843       | -0.249 (0.804)   |
| Pfixbb               | -0.013       | -2.559 (0.011)   |
| Pritage              | -0.324       | -1.226 (0.221)   |
| Onlnserv             | 22.972       | 2.120 (0.035)    |
| PCapelec             | 0.542        | 5.060 (0.000)    |
| Dlspeed              | 0.400        | 4.330 (0.000)    |
| Skill                | 0.256        | 1.556 (0.120)    |
| \([\text{Supply-side}]\) |              |                    |
| PopDens              | 0.004        | 4.908 (0.000)    |
| Urban                | 0.135        | 2.184 (0.030)    |
| \([\text{Policy factors}]\) |         |                    |
| HHI                  | -15.960      | -1.310 (0.191)   |
| ServComp             | -2.930       | -1.665 (0.097)   |
| ICTlaw               | 6.547        | 1.650 (0.099)    |
| CrptMgt              | 0.328        | 6.182 (0.000)    |
| Devictax             | -0.112       | -2.937 (0.003)   |
| \([\text{Newly added}]\) |              |                    |
| Femlabor             | 0.210        | 11.909 (0.000)   |
| SoftPrc              | -0.198       | -1.193 (0.234)   |
| AppFlag              | -0.092       | -0.671 (0.000)   |
| GovPro               | 5.414        | 1.711 (0.242)    |
| MbbCov               | 0.162        | 2.366 (0.018)    |
| Spectrm              | 0.099        | 6.070 (0.000)    |
| Take-off             | -16.871      | -9.136 (0.000)   |
| Saturated            | 32.535       | 11.665 (0.000)   |

Model significance:

- Degrees of freedom: 436
- F-statistics: 72.4 (p-value: 0.0000)
- Adjusted \( R^2 \): 0.7815

- Degrees of freedom: 434
- F-statistics: 107.8 (p-value: 0.0000)
- Adjusted \( R^2 \): 0.8533

where \( y \) is mobile broadband adoption; \( \beta_0 \)'s are intercepts; \( x_i \)'s explanatory variables; \( \beta_i \)'s the coefficients of the explanatory variables; \( f = 1 \) for the Take-off group, 2 for the Fast-diffusion group, and 3 for the Saturated group; \( t = 2013, \ldots, 2016 \); and \( u_\mu \) and \( v_\mu \) are disturbances which are independently and identically distributed with zero mean and constant variances.

The LSDV model with interactions:

\[
\text{Pooled model: } y_\mu = \beta_{0j} + \sum_{i=1}^{23} \beta_i x_{ij} + u_\mu \\
\text{LSDV model: } y_\mu = \beta_{0j} + \sum_{i=1}^{23} \beta_i x_{ij} + v_\mu
\]

where \( D_1 \) is a dummy variable for group 1 and for group 3, and \( w_\mu \sim \text{iid}(0, \sigma^2) \).

We use all 23 explanatory variables and a constant in the pooled model, and, additionally, two dummy variables for the Take-off and Saturated groups in the LSDV fixed effect model, indicating that the Fast-diffusion group is used as the reference group. We then run 23 LSDV fixed effect models with interaction terms, separately as shown in Eq. (3). Given that one objective of this paper is to investigate differential policy effects on mobile broadband adoption, we run 23 LSDV models, each of which has one policy variable interaction term with group dummies. The reason why we run separate 23 LSDV models, rather than putting all interaction terms in a regression model, is to avoid the dummy variable trap that we are likely to encounter when putting many slope interaction terms in a model at the same time (Gujarati & Porter, 2009, p. 598).
4. Results of analyses

4.1. Effects on mobile broadband adoption: pooled and fixed effect models

We run a pooled and LSDV fixed effect models with a statistical package, R (version 3.4.3), to check if the coefficients of regression models are statistically significant and are congruent with the expected signs in Table 1. When heterogeneous group samples are mixed, it is well-known that the coefficients of the pooled model are likely to be biased. There have been two approaches to handling between-group heterogeneity: one is to introduce group dummies to the pooled model, the model of Eq. (2), and the other is to use the model of Eq. (3). The former model is also called a fixed effect model and the latter a fixed effect model with interaction terms. The regression results of the pooled and LSDV fixed effect models are presented in Table 4 and those of a fixed effect model with interaction terms are discussed in the following subsection, 4.2. Before running the regressions, we calculated the pairwise correlation coefficients among the explanatory variables and present the correlation coefficients in Appendix 4, which reveals that multicollinearity is not likely to be a serious problem because the maximum of pairwise correlation coefficients is 0.87 and only three values are in between 0.8 and the maximum. Surely, pairwise correlation coefficients are neither necessary nor sufficient for avoiding the multicollinearity problem. Therefore, we calculated the variance inflating factor (VIF) for the pooled model and found that only one variable, Compu, has a VIF of 12.2 and all other variables have VIF values far less than 10. This finding indicates that multicollinearity is not a serious problem in these regression analyses (Gujarati & Porter, 2009, p. 340).

The dataset used in this paper is a short panel with a much greater number of cross-sectional units (115) than that of time periods (four years). Therefore, autocorrelation is not likely to be a problem but heteroscedasticity is likely to exist. It is a well-known fact that even in the presence of heteroscedasticity, estimated coefficients are unbiased, but they are inefficient. Thus, this paper makes corrections for the standard errors of pooled and fixed effect regression models with the coeftest and vcovHC function in R software. Put differently, the t-values and p-values in Table 4 for both models are White’s heteroscedasticity corrected standard errors. In both models of Table 4, either the time trend variable or the year dummies are not included because it is difficult to consider the possibility that there was a common time trend globally or a year specific event that affected all countries from 2013 to 2016.

The results of the pooled model show that the coefficients of 13 of the 23 variables, excluding the constant, are statistically significant at the 5% level of significance and three of them are at the 10% level of significance. Among those statistically significant explanatory variables, the following eleven variables turned out to be positively related to mobile broadband adoption (diffusion): computer availability (Compu), the quality of e-government services (Onlnserv), electricity use (PCapelec), mobile broadband download speed (Dlspeed), population density (PopDens), urbanization rate (Urban), level of corruption (CrptMgt, increasing means less corruption), ICT law completeness (ICTlaw), female labour participation rate (Femlabor), mobile broadband coverage (MbbCov), and spectrum amount (Spctrm). Tariffs on fixed broadband (Pfixbb) and fixed broadband subscription rates (Fixbbsub) were found to have a negative relationship with mobile broadband diffusion, implying that the results are contradictory. The negative sign of the fixed broadband tariff means that fixed and mobile broadband services are complements, but that of fixed subscription rate suggests that they are substitutes. The relationship between fixed and mobile broadband may vary with mobile broadband diffusion. For example, when both services are available, they could be substitutes in low-income countries, because users might choose one of the two to reduce expenditure on broadband subscription, but they could be complements in high-income countries.

8 VIF values: Pcapinc (4.27), Compu (12.20), Fixbbsub (8.25), Pmobb (1.35), Pfixbb (1.31), Prdtage (3.24), Onlnserv (1.61), PCapelec (2.11), Dlspeed (3.63), Skill (5.72), PopDens (1.34), Urban (3.19), HHI (1.31), ServComp (1.36), ICTlaw (3.84), CrptMgt (1.08), Devictax (1.56), Femlabor (1.33), SoftPrc (5.97), AppFlag (2.43), GovPro (3.12), MbbCov (3.26), Spctrm (1.06).

9 The coeftest function uses the variance-covariance matrix calculated by vcovHC in order to make corrections for standard errors.
countries because of bundling strategies of firms. This differential effect along diffusion stages are further discussed in the following subsection. Device tax, as expected, has a negative effect on mobile broadband adoption, but, against our expectations, per capita income and secondary education level (Skill) are not statistically significant. Our finding regarding service competition level is also not statistically significant, and application availability in the first language (AppFlag) has a statistically significant but opposite positive influence mobile broadband adoption, but software piracy rate (SoftPrc) and government promotion effort (GovPro) are not statistically significant, and HHI is insignificant with the expected sign, implying that, on average, market competition effects are not satisfactory in this analysis.

Among the six newly added variables, female labor participation rate, spectrum amount, and mobile broadband coverage positively influence mobile broadband adoption, but software piracy rate (SoftPrc) and government promotion effort (GovPro) are not statistically significant, and application availability in the first language (AppFlag) has a statistically significant but opposite sign, against our expectation. Mobile broadband coverage, as discussed before, is not a sufficient but necessary condition for mobile broadband diffusion, and the result of the pooled model supports this argument.

| Variables      | Take-off                  | Fast-diffusion (reference group) | Saturated                  | Model significance |
|----------------|---------------------------|----------------------------------|----------------------------|--------------------|
|                | Coeff. (t-value (p-value))| Coeff. (t-value (p-value))      | Coeff. (t-value (p-value))|                    |
| PCapinc        | 0.224 (0.888 (0.375))     | 0.048 (2.332 (0.020))           | -0.208 (-28.507 (0.000))  | 100.6 (0.854)      |
| Compu          | -0.144 (-3.800 (0.000))   | 0.310 (11.894 (0.000))          | -0.511 (-7.014 (0.000))   | 101.2 (0.855)      |
| Fixbssub       | 0.094 (0.479 (0.632))     | -0.228 (-1.016 (0.310))         | -0.526 (-1.982 (0.048))   | 100.9 (0.855)      |
| Pmobb          | -1.361 (-8.033 (0.422))   | -1.471 (-9.064 (0.367))         | -19.870 (-7.461 (0.000))  | 100.2 (0.854)      |
| Pfubb          | 0.161 (6.378 (0.000))     | -0.167 (-5.918 (0.000))         | -0.223 (-3.161 (0.002))   | 103.1 (0.857)      |
| Prdtype        | 0.383 (0.959 (0.338))     | -0.540 (-3.682 (0.000))         | -0.054 (-0.644 (0.520))   | 99.81 (0.853)      |
| Onlnserv       | -36.294 (-19.317 (0.000)) | 44.125 (25.714 (0.000))         | -17.488 (-4.313 (0.000))  | 106.4 (0.861)      |
| Pcapeco        | -1.765 (-4.671 (0.000))   | 0.542 (2.012 (0.045))           | -0.402 (-1.770 (0.077))   | 101.8 (0.855)      |
| Dispeed        | -0.183 (-1.175 (0.241))   | 0.301 (3.111 (0.002))           | 0.039 (0.438 (0.662))     | 99.65 (0.853)      |
| Skill          | -0.226 (-10.705 (0.000))  | 0.346 (5.317 (0.000))           | -0.443 (-3.875 (0.000))   | 102.6 (0.857)      |
| Ppopdens       | 0.0366 (3.497 (0.001))    | -0.0365 (-3.657 (0.000))        | 0.0396 (3.617 (0.000))    | 104.9 (0.859)      |
| Urban          | -0.070 (-2.192 (0.029))   | 0.017 (0.385 (0.701))           | 0.204 (2.997 (0.037))     | 99.93 (0.853)      |
| HHI            | 16.317 (4.350 (0.000))    | -13.370 (-23.749 (0.000))       | 24.850 (0.548 (0.884))    | 99.79 (0.853)      |
| Servcomp       | -1.100 (-1.486 (0.138))   | -0.286 (-0.810 (0.418))         | -6.846 (-3.029 (0.003))   | 99.9 (0.853)       |
| ICTlaw         | 2.728 (1.445 (0.150))     | -1.968 (-1.130 (0.259))         | 7.253 (7.737 (0.000))     | 100.4 (0.854)      |
| Cntrtmg        | -1.178 (-8.052 (0.000))   | 0.933 (3.200 (0.001))           | 0.106 (0.167 (0.867))     | 99.58 (0.853)      |
| Devicatx       | 0.015 (0.266 (0.791))     | -0.151 (-2.865 (0.004))         | 0.457 (12.358 (0.000))    | 101.5 (0.855)      |
| Femlabor       | 0.194 (26.604 (0.000))    | -0.015 (-0.342 (0.732))         | -0.261 (-0.812 (0.417))   | 100.8 (0.855)      |
| SoftPrc         | 0.083 (8.361 (0.000))    | -0.100 (-1.329 (0.185))         | 0.091 (3.605 (0.002))     | 99.56 (0.853)      |
| AppFlag         | -0.045 (-3.900 (0.000))   | -0.046 (-6.057 (0.000))         | 0.114 (3.516 (0.001))     | 100.5 (0.854)      |
| GovPro          | 0.416 (0.261 (0.794))     | -1.834 (-0.902 (0.368))         | 4.977 (3.215 (0.001))     | 100.3 (0.854)      |
| MbbCov         | -0.201 (-12.962 (0.000))  | 0.285 (6.612 (0.000))           | 8.190 (8.062 (0.000))     | 104.1 (0.858)      |
| Spectr         | -0.028 (-20.674 (0.000))  | 0.081 (31.534 (0.000))          | 0.077 (6.330 (0.000))     | 99.72 (0.853)      |

* Statistically significant coefficients are in bold.

In panel data analysis, the random effect model can be used instead of the fixed effect model. Conceptually, the random effect model is appropriate when countries in the dataset of this paper are randomly assigned to three groups. In this paper, countries are assigned to three groups by the K-means clustering method, implying that they are not randomly assigned to three groups. In addition, we ran the Hausman test to see if the fixed effect model is better for our dataset than the random effect model and found that the estimated chi-squared value is 407.8 with 23 degrees of freedom (p-value = 0.00000), showing that we can reject the random effect model.
4.2. Estimating differential effects on mobile broadband adoption

In government policy studies, it is a well-supported axiom that one size does not fit all. This logic can also be applied to mobile broadband services. As the mobile broadband diffusion level changes, the policy mix needs to change as well because market constraints, affecting demand and supply in the market, often vary with the growth of mobile broadband markets. In order to estimate how explanatory variables affect differentially mobile broadband diffusion, we ran 23 fixed effect models separately, each of which had an interaction term with group dummy variables, say, HHI * Take-off and HHI * Saturated. The reference group is Fast-diffusion, and even though all 23 variables may not be treated as policy variables in countries, this paper ran 23 fixed effect regression models with different interaction terms. Table 5 reports the outcomes of 23 regressions, in which the reference group results are comparable to those of the fixed effect model, as shown in Table 4.

Out of 23 explanatory variables, when interacted with group dummies, 15 variables of the reference group turned out to be statistically highly significant and adjusted R² increased slightly after adding interaction terms. Those statistically significant variables can be identified by bold t-values in Table 5, and the coefficients underlined are the cases in which the signs of coefficients are against the expected ones.

Table 5 delivers many new analytical outcomes, not reported before in previous studies. In Table 4, we identified differential intercepts for three groups, which was obviously not a surprising result because we clustered all sample countries into three groups by mobile broadband diffusion rate and speed. What is important here is to determine which explanatory (policy) variables were effective in the three mobile broadband stages, so that we help policy makers make better policy mixes in the development stages of mobile broadband. Because individual variables’ effects on mobile broadband adoption have been already discussed in the previous subsection, we here focus on explaining differential effects. Care should be taken in interpreting the differential slopes, the coefficients of Take-off and Saturated groups in Table 5. The coefficients of the Take-off and Saturated groups measure the differences from the corresponding slope of the reference group and their t-values test if the differences are statistically significantly different from zero. For example, the differential slopes of the spectrum in Table 5 are 0.028 for the Take-off group and 0.077 for Saturated, implying that the gross values of the two groups are 0.053 and 0.158, respectively. Therefore, a negative value of a differential slope does not necessarily mean that its gross effect is negative. In other words, more spectrum is helpful for increasing mobile broadband adoption without regard to the level of mobile broadband diffusion. In addition, this paper found that the effect of more spectrum supply on mobile

Table 6
Effective policy variables for three groups.

| Group            | Effective policy variables                                                                 |
|------------------|---------------------------------------------------------------------------------------------|
| Take-off (6)     | Computer (Compu), Download speed (DLspeed), Population density (PopDens), Secondary education level (Skill), Female labor participation rate (Femlabor), Spectrum (Spectrm) |
| Fast-diffusion (10) | Per capital income (PCapinc), Compu² (Compu), Fixed broadband tariff (Pfixbb), Quality of e-government services (Onlnserv), Electricity consumption (PCapelec), Download speed (DLspeed), Secondary education level (Skill), Market competition (HHI), Device tax (Devictax), Spectrum (Spectrm) |
| Saturated (13)   | Tariff of mobile broadband service (Pmobbb), Fixed broadband tariff (Pfixbb), Quality of e-government services (Onlnserv), Electricity consumption (PCapelec), Download speed (DLspeed), Population density (PopDens), Urbanization rate (Urban), ICT law completeness (ICTlaw), Corruption perception level (CrptMgt), Applications in the first language (AppFalg), Government promotion performance (GovPro), Mobile broadband coverage (MbbGov), Spectrum (Spectrm) |

* Policy variables in bold font are unique ones in each group, those underlined are common in all groups, and those superscripts are common only in Take-off and Fast-diffusion.

Fig. 3. Differential effects of mobile broadband coverage.

4.2. Estimating differential effects on mobile broadband adoption

Table 5 reports only the coefficients of interaction terms and omits other coefficients to enhance legibility.
broadband adoption becomes stronger in a country as the country proceeds from Take-off to Fast-diffusion and to Saturated. This outcome exactly corresponds to our expectation and experience because spectrum becomes scarcer as the number of subscriber grows (Kwon et al., 2017; Kwon & Kim, 2012).

Mobile broadband coverage measures the supply of mobile broadband service in a country and, as discussed earlier, increasing mobile broadband coverage does not always entail a higher mobile broadband subscription rate, especially when demand is stagnant. From Tables 4 and 5, we can consistently observe that mobile broadband coverage is positively correlated with mobile broadband adoption, without regard to analytical models used. Table 5 and Fig. 3 reveal in more detail that mobile broadband coverage in the Take-off and Fast-diffusion groups has almost no effect and a very small effect, respectively, on the mobile broadband subscription rate. They also show that the coefficient of the Saturated group is about 30 times greater than that of the Fast-diffusion group, showing that mobile broadband coverage is one of the key factors for enhancing mobile broadband diffusion, especially in Saturated countries. Putting this differently, increasing mobile broadband coverage is effective mainly in Saturated countries, suggesting that demand rather than supply should be a key policy concern of the Take-off and Fast-diffusion group countries for mobile broadband diffusion.

We can also observe from Table 5 that income positively affects mobile broadband adoption in the Fast-diffusion and Take-off stages, and computer availability is effective in both the Take-off and Fast-diffusion stages, with its effect being stronger in the Fast-diffusion stage, while it is not an effective policy for the Saturated group. It is also shown that a mobile broadband tariff has a negative relationship with mobile broadband diffusion only in the Saturated group and that the relationship between mobile and fixed broadband services turns out to be complementary in all groups, with the strongest complementarity in the Saturated group. The quality of e-government services (Onlineserv) had strong and moderate positive effects on mobile broadband adoption in the Fast-diffusion and Saturated groups, respectively. Electricity consumption per person (PCapelec) is positively correlated with mobile broadband use in the Fast-diffusion and Saturated groups, being most strongly correlated in the Fast-diffusion group and moderately in the Saturated one. Mobile internet download speed (Dlspeed) is positively correlated with the mobile broadband adoption rate in all models in Tables 4 and 5, and we can also see in Table 5 that statistically there is no difference in its effect among the three groups.

Population density (PopDens) is also positively correlated with the mobile broadband adoption rate in the Take-off and Saturated groups, but negatively correlated in the Fast-diffusion group. This may imply that at the Fast-diffusion stage, demand factors are more important than supply factors because population density is a supply factor. Urbanization rate (Urban), another supply factor, is not statistically significant in the fixed effect model, but we can find that it increases the mobile broadband adoption rate in the Saturated group. A higher market competition level (HHI) turns out to be helpful for the Fast-diffusion and Saturated groups, but the opposite result was derived for the Take-off group, suggesting that an oligopolistic market structure might be better for improving the mobile broadband adoption rate at an early stage of mobile broadband services. One finding that cannot be easily interpreted in the analyses of this paper is that the level of service competition (ServComp), against theoretical expectation, has a negative correlation with mobile broadband adoption rate in the two models of Table 4 and a strong negative correlation, especially in the Saturated group. The software piracy rate (SoftPrc, one-year lag variable) shows no effects on mobile broadband adoption rate in all groups although its coefficients for the Take-off and Saturated groups are statistically significantly different from that of the reference group. The population rate with mobile apps in their first language (AppFlag) and government promotion performance (GovPro) seem to have no effect on the mobile broadband adoption rate according to Table 4, but they turn out to have positive effects on mobile broadband adoption only in the Saturated group.

5. Discussions and implications

5.1. Discussion on effective policy measures along diffusion stages

The analytical outcomes of this paper, introduced in Tables 4 and 5, reconfirm that the findings of previous literature are still by and large valid, and this paper also finds that five variables (Femlabor, Flag, AppFlag, GovPro, MbbCov, and Spctrm) among the six newly added variables are positively correlated with mobile broadband adoption in all groups or a group. The software piracy rate variable is the exception, showing no effect on mobile broadband adoption. This finding, however, should not be interpreted as evidence that software piracy regulations have had no effects on mobile broadband adoption in light of the fact that this paper is one empirical research study with a limited dataset covering only four years. It would be, therefore, premature to generalize the outcomes of this research, the results of which should be evaluated with care. Specifically, the female labor participation rate is an effective policy tool only for the Take-off group, and spectrum supply for all three groups. The remaining three policy variables (AppFlag, GovPro, and MbbCov) are also effective policy tools only for the Saturated group.

Based on the findings of the previous section, this paper classifies effective policy variables for the three groups in Table 6. First, out of 23 policy variables, 20 variables were identified as effective policy variables either in one group or multiple groups. Mobile internet download speed and spectrum supply are effective policy tools for all groups, computer and secondary education level only for the Take-off and Fast-diffusion groups, and fixed broadband tariff, quality of e-government services and electricity consumption are effective policy tools only for the Fast-diffusion and Saturated groups. Even though population density is shown to be an effective tool for the Take-off and Saturated groups, it cannot be easily and quickly altered by governments, so it is hard to consider it as a useful policy tool. Second, among the three groups, considerable gaps exist in the size of effective policy choice sets: six for Take-off, ten for Fast-diffusion, and thirteen for Saturated, supporting our initial hypothesis, set forth in the Introduction, that as a mobile broadband market matures, market constraints hindering mobile broadband adoption weaken. This disparity in the size of policy choice sets also suggests that the countries in the Take-off stage have a narrow degree of latitude for developing mobile broadband promotion.
strategies. Among the six effective policy tools, only computer supply is a short-term policy tool for governments in the Take-off group, making the odds of overcoming the global digital divide dismal. Thirdly, this paper identified an interesting finding that each group has unique policy variables, as shown in bold font in Table 6: one for Take-off, three for Fast-diffusion, and six for Saturated, implying that the degree of latitude in devising mobile broadband policy mix increases with market size (mobile broadband adoption rate). The average value of the female labor participation rate for Take-off is the lowest among the three groups, so it is likely to be an effective policy variable for the Take-off group in improving mobile broadband adoption rate, but not for the other two groups. Fourthly, for those in the Take-off group to successfully move into the Fast-diffusion group, they should focus on policy variables effective for the Fast-diffusion group. Specifically, they need to put their efforts into economic development, education, computer and electricity supply, and online content supply, while increasing competition in their mobile broadband markets and facilitating investments in fixed and mobile broadband networks. Fifthly, it is recommended that those in the Fast-diffusion group focus on the six unique variables in order to climb up to a Saturated group: lowering mobile broadband service tariff by enhancing competition (Pmobb), increasing mobile broadband coverage (MbbCov), providing more application in their first languages (AppFlag), exerting more government efforts for promoting ICT industries (GovPro), improving the level of the ICT law completeness (ICTlaw), and reducing the corruption level (CrptMgt). Finally, Table 6 also shows that the quality of e-government services appears first in the Fast-diffusion stage and applications in the first language appear first in the Saturated stage along with the quality of e-government, confirming our expectation that content diversity and availability become more important when a country has arrived at the Fast-diffusion and Saturated stages consecutively, i.e., a country’s mobile broadband market matures.

5.2. Policy and managerial implications

This paper evaluates the mobile broadband development policies within the framework of a coherent and comprehensive ecosystem by appraising their roles in terms of supply and demand components. It has been well noted that access to digital services and content through mobile broadband networks, such as e-commerce, e-health, e-finance, online education, streaming services, and disaster relief, has become critical for people’s economic wellbeing, especially now, during the ongoing Covid-19 pandemic disaster. There are, however, indications of a growing, rather than declining, urban-rural divide within developed countries and a global digital divide between countries in terms of access to broadband. Bridging these divides requires tailored policy-mixes across diffusion stages as follows.

5.2.1. Take-off stage

This study shows that developing markets for broadband networks and services should be given emphasis by fostering demand, especially in the early two stages of diffusion. The Take-off stage requires more emphasis in creating the demand side of the market relative to other stages, as evidenced by the study findings. Although the supply side of the market is important, simply building networks does not guarantee broadband adoption. Promotion of computer ownership, skill development, and enhancing female labor participation and download speed are important factors because they constitute necessary and sufficient contributions in expanding broadband markets.

5.2.2. Fast-diffusion stage

In this stage, governments need to put emphasis on continuing to promote computer ownership, download speed and skill development and further strengthening the purchasing power of the consumers by improving GNI per capita. In addition, reducing device taxes, supply spectrum in a timely manner, and boosting competition in mobile broadband markets turned out to be effective, especially in this second stage, for promoting demand for mobile broadband adoption.

5.2.3. Saturated diffusion stage

As the broadband market matures, mobile broadband price, download speed, urbanization and population density arise as important factors for inclusive mobile broadband diffusion. Furthermore, governments in this stage need to pursue reinforcing sound and strong institutions through controlling corruption, creating a conducive environment to attract new investment on network coverage (connectivity), and strengthening legal foundations by revamping ICT laws. It should also be noted that enriching applications in the first language and supplying more spectrum without delays are critical for fortifying indirect network effects in mobile broadband ecosystems (Kwon & Cho, 2015).

5.2.4. Lessons for new disruptive technology diffusion

This study shows that developing countries should foster demand first, rather than supply, in order to catch-up, and this strategy is applicable to other new technology areas as well. The information and communication technology (ICT) ecosystem, composed of multi-layers of devices, networks, platforms and content, will continue to evolve more rapidly than ever before as new disruptive technologies such as artificial intelligence (AI) and quantum technologies become widespread (Feijoo et al., 2020; Feijoo & Kwon, 2020). In particular, the gap between developed and developing countries in the development and use of AI technologies is widening rapidly because funds and talents for developing those technologies are lacking in developing countries. However, most AI development software is open-source and available to everyone (Feijoo et al., 2020). Thus, AI service diffusion can be triggered even in developing countries if governments can create demand for AI services and raise local talents in their markets, eventually narrowing the divide in AI service markets between developed and developing countries.
6. Conclusions

This paper utilized a short panel dataset with 115 countries’ annual observations over four years from 2013 to 2016 and evaluated which policies were more effective than others along the three stages of mobile broadband diffusion. The large dataset size allowed us to perform fixed effect model analyses with interaction terms, revealing that countries in different stages of mobile broadband adoption need different mobile broadband policy mixes. These differential effects have never been studied in the previous research, mainly because such a dataset as the one we constructed was not available before. We believe the research outcomes of this paper have the potential to help policy makers in developing countries devise various policy mixes best suitable for their countries. This paper drew on the K-means clustering method, an unsupervised learning algorithm, in classifying 115 countries into three groups: Take-off, Fast-Diffusion and Saturated. In clustering countries, we used not just the mobile broadband diffusion level but also the average speed of mobile broadband diffusion over the four years. This is also a new approach taken for grouping of countries.

Our new dataset and analytical methods revealed new knowledge, potentially useful for overcoming the global digital divide. It is found that Take-off group countries, comprised of mostly underdeveloped countries, have the least degree of latitude in developing mobile broadband promotion policies, whereas Saturated group countries have an ample set of policy choices. It is also found that those in the Take-off group, to successfully ladder up to the Fast-diffusion stage should put their efforts into economic development, education, computer and electricity supply, and online content supply, while increasing competition in their mobile broadband markets and facilitating investments in fixed and mobile broadband networks. As this work remains only one empirical research study with the application of new methodology, the outcomes cannot be overly generalized.

Appendix 1. Clustering countries by mobile broadband diffusion level and its speed

|                | Country                      | Average MBB diffusion (%) | MBB diffusion speed (%/4yrs) | Per capita GNI ($) |
|----------------|------------------------------|---------------------------|------------------------------|-------------------|
| Take-off (47)  | Albania, Bangladesh, Bolivia, Cambodia, Cyprus, Dominica, El Salvador, Ethiopia, Gambia, Georgia, Guatemala, Honduras, Hungary, India, Indonesia, Iran, Jordan, Kenya, Lesotho, Madagascar, Malawi, Mali, Mauritania, Mauritius, Mexico, Montenegro, Morocco, Mozambique, Namibia, Nepal, Nicaragua, Nigeria, Pakistan, Panama, Paraguay, Peru, Philippines, Rwanda, Senegal, Sri Lanka, Swaziland, Tanzania, Trinidad, Uganda, Ukraine, Vietnam, Zambia |
| Fast-diffusion (49) | Argentina, Austria, Azerbaijan, Belgium, Botswana, Brazil, Bulgaria, Canada, Chile, China, Colombia, Costa Rica, Croatia, Czech Republic, Egypt, France, Germany, Ghana, Greece, Israel, Italy, Jamaica, Kazakhstan, Kyrgyz Republic, Latvia, Lebanon, Lithuania, Macedonia, Malaysia, Moldova, Mongolia, Netherlands, Oman, Poland, Portugal, Romania, Russia, Saudi Arabia, Serbia, Slovak, Slovenia, South Africa, Spain, Switzerland, Thailand, Turkey, Uruguay, Venezuela, Zimbabwe |
| Saturated (19) | Australia, Denmark, Estonia, Finland, Hong Kong, Iceland, Ireland, Japan, South Korea, Kuwait, Luxembourg, Malta, New Zealand, Norway, Qatar, Singapore, Sweden, United Kingdom, United States |

Appendix 2. Sample countries and their three key variables

| Country | Average MBB diffusion (%) | MBB diffusion speed (%/4yrs) | Per capita GNI ($) | Country | Average MBB diffusion (%) | MBB diffusion speed (%/4yrs) | Per capita GNI ($) |
|---------|--------------------------|-----------------------------|-------------------|---------|--------------------------|-----------------------------|-------------------|
| Albania | 21.7                     | 22.1                        | 4270              | Macedonia | 32.7                     | 31.4                        | 5198              |
| Argentina | 29.6                  | 41.9                        | 13827             | Madagascar | 2.4                      | 6.0                         | 428               |
| Australia | 98.0                   | 39.3                        | 57467             | Malawi | 3.6                      | 1.0                         | 325               |
| Austria | 57.6                     | 24.6                        | 47895             | Malaysia | 24.1                     | 46.1                        | 10230              |
| Azerbaijan | 40.4                  | 40.0                        | 6267              | Mali | 3.5                      | 11.0                        | 788               |
| Bangladesh | 3.9                     | 13.4                        | 1237              | Malta | 75.3                      | 4.2                         | 24818              |
| Belgium | 39.0                     | 38.4                        | 44047             | Mauritania | 7.1                      | 10.8                        | 1413              |
| Bolivia | 12.9                     | 25.3                        | 3090              | Mauritius | 24.0                     | 19.3                        | 9683              |
| Botswana | 52.6                   | 63.2                        | 7002.5            | Mexico | 17.7                      | 34.6                        | 10055              |
| Brazil | 46.0                     | 57.2                        | 10475             | Moldova | 26.3                      | 45.8                        | 2410               |
| Bulgaria | 50.7                    | 36.5                        | 7525              | Mongolia | 27.9                      | 40.3                        | 4053               |
| Cambodia | 12.4                    | 28.8                        | 1132              | Montenegro | 24.2                     | 15.6                        | 7033               |
| Canada | 46.2                     | 15.9                        | 47295             | Morocco | 15.0                      | 18.8                        | 3105               |
| Chile | 33.0                     | 32.5                        | 14425             | Mozambique | 1.9                      | 1.9                         | 533                |
| China | 22.4                     | 32.3                        | 7767              | Namibia | 30.6                      | 13.3                        | 5383               |
| Colombia | 19.7                   | 41.4                        | 6997              | Nepal | 13.0                      | 23.7                        | 720                |
| Costa Rica | 45.1                  | 83.3                        | 11127             | Netherlands | 60.5                     | 20.1                        | 49088              |
| Croatia | 55.7                     | 33.7                        | 12855             | New Zealand | 73.2                     | 39.7                        | 40628              |
| Cyprus | 34.8                     | 11.4                        | 25527             | Nicaragua | 1.1                      | 0.5                         | 2010               |
| Czech | 53.6                     | 23.3                        | 18975             | Nigeria | 12.6                      | 8.5                         | 2820               |
|         |                          |                             |                   | Denmark | 106.7                    | 15.3                        | 57767              |
|         |                          |                             |                   | Norway | 106.7                    | 2.3                         | 86123              |
|         |                          |                             |                   | Dominican Republic | 19.7                    | 22.4                        | 7610              |
|         |                          |                             |                   | Oman | 57.4                      | 35.9                        | 19605              |
|         |                          |                             |                   | Egypt | 31.7                      | 19.5                        | 3585               |
|         |                          |                             |                   | Pakistan | 1.6                      | 4.9                         | 1360               |
|         |                          |                             |                   | El Salvador | 8.4                      | 14.9                        | 3640               |
|         |                          |                             |                   | Panama | 20.9                      | 15.2                        | 13300              |
### Appendix 3. Descriptive statistics of 24 independent variables

| Variable   | Mean   | Standard Deviation | Minimum | Maximum |
|------------|--------|--------------------|---------|---------|
| Bhadopt    | 37.92  | 33.46              | 0.02    | 139.33  |
| PCapinc    | 17.86  | 21.82              | 0.29    | 120.86  |
| Compu      | 47.53  | 30.66              | 0.20    | 98.10   |
| Fixbbsub   | 13.21  | 12.49              | 0.01    | 42.52   |
| Pmobb      | 0.29   | 0.20               | 0.01    | 1.23    |
| Pfixbb     | 50.18  | 95.55              | 2.59    | 1040.24 |
| Prdtaige   | 64.90  | 5.98               | 49.06   | 85.48   |
| Onlnserv   | 0.57   | 0.20               | 0.01    | 0.98    |
| PCapelec   | 4.73   | 6.58               | 0.00    | 55.95   |
| Dispeed    | 18.06  | 20.95              | 0.04    | 100.00  |
| Skill      | 85.40  | 25.19              | 24.44   | 163.10  |
| Pop        | 56.40  | 177.06             | 0.33    | 1382.71 |
| PopDens    | 273.63 | 964.02             | 1.85    | 7908.72 |
| Urban      | 62.70  | 22.55              | 8.35    | 100.00  |
| HHI        | 0.12   | 0.10               | 0.03    | 0.78    |
| ServComp   | 1.72   | 0.43               | 0.00    | 2.00    |
| ICTlaw     | 3.10   | 0.65               | 1.98    | 4.98    |
| CrptMgt    | 0.17   | 1.0                           1.40 | 2.34 |
| Devicetax  | 39.53  | 15.83              | 7.40    | 100.00  |
| Femlabor   | 52.51  | 13.80              | 12.40   | 91.31   |
| SoftPrc    | 60.70  | 21.18              | 18.00   | 93.00   |
| AppFlag    | 65.53  | 41.01              | 0.03    | 99.99   |
| GovPro     | 4.31   | 0.83               | 2.89    | 6.97    |
| MbbCov     | 83.76  | 20.85              | 15.94   | 100.00  |
| Spctrm     | 41.33  | 19.47              | 0.00    | 100.00  |
Appendix 4. Pairwise correlation table for explanatory variables

|                  | Peapinc | Compu | Fixbbsub | Pmobb | Pfixbb | Prdtage | Onlnserv | Peapelec | Dlspeed | Skill | Pop | PopDens | Urban | HHI | Serv | ICTlaw | CrptMgt | Devictax | SoftPrc | GovPro | MbbCov | Spectrm | App | Femlabor |
|------------------|---------|-------|----------|-------|--------|---------|----------|----------|---------|-------|-----|--------|-------|-----|------|--------|--------|----------|--------|--------|--------|--------|-----|----------|
| Peapinc          | 1       |       |          |       |        |         |          |          |         |       |     |        |       |     |      |        |        |          |        |        |        |        |     |          |
| Compu            | 0.77    | 1     |          |       |        |         |          |          |         |       |     |        |       |     |      |        |        |          |        |        |        |        |     |          |
| Fixbbsub         | 0.78    | 0.87  | 1        |       |        |         |          |          |         |       |     |        |       |     |      |        |        |          |        |        |        |        |     |          |
| Pmobb            | -0.1    | -0.1  | 0.0      | 1     |        |         |          |          |         |       |     |        |       |     |      |        |        |          |        |        |        |        |     |          |
| Pfixbb           | -0.1    | -0.3  | -0.2     | 0.1   | 1      |         |          |          |         |       |     |        |       |     |      |        |        |          |        |        |        |        |     |          |
| Prdtage          | 0.4     | 0.6   | 0.4      | -0.2  | -0.4   | 1       |          |          |         |       |     |        |       |     |      |        |        |          |        |        |        |        |     |          |
| Onlnserv         | 0.3     | 0.4   | 0.4      | 0.0   | -0.1   | 0.1     | 1        |          |         |       |     |        |       |     |      |        |        |          |        |        |        |        |     |          |
| Peapelec         | 0.6     | 0.6   | 0.76     | -0.2  | -0.2   | 0.3     | 0.5      | 0.6      |        |       |     |        |       |     |      |        |        |          |        |        |        |        |     |          |
| Dlspeed          | 0.6     | 0.7   | 0.76     | -0.2  | -0.2   | 0.3     | 0.5      | 0.6      | 1      |       |     |        |       |     |      |        |        |          |        |        |        |        |     |          |
| Skill            | 0.6     | 0.81  | 0.7      | -0.1  | -0.3   | 0.7     | 0.4      | 0.5      | 0.6    | 1     |     |        |       |     |      |        |        |          |        |        |        |        |     |          |
| Pop              | 0.1     | -0.1  | -0.1     | -0.2  | -0.1   | 0.1     | 0.0      | -0.1     | 0.0    | -0.1  | 1   |        |       |     |      |        |        |          |        |        |        |        |     |          |
| PopDens          | 0.2     | 0.2   | 0.2      | -0.1  | 0.0    | 0.2     | 0.0      | 0.0      | 0.2    | 0.1   | 0.0 | 1       |       |     |      |        |        |          |        |        |        |        |     |          |
| Urban            | 0.6     | 0.7   | 0.6      | 0.1   | -0.2   | 0.5     | 0.3      | 0.5      | 0.7    | -0.1  | 0.2 | 1       |       |     |      |        |        |          |        |        |        |        |     |          |
| HHI              | -0.1    | -0.2  | -0.2     | 0.1   | 0.1    | 0.0     | -0.1     | -0.1     | -0.1   | -0.1  | 0.0 | 1       |       |     |      |        |        |          |        |        |        |        |     |          |
| ServComp         | 0.2     | 0.2   | 0.3      | 0.0   | -0.1   | 0.1     | 0.2      | 0.0      | 0.1    | 0.2   | 0.0 | 1       |       |     |      |        |        |          |        |        |        |        |     |          |
| ICTlaw           | -0.5    | -0.6  | -0.6     | 0.2   | 0.1    | -0.4   | -0.3     | -0.3     | -0.5   | -0.6  | -0.1 | -0.5    | 0.2     | 0.4 | 1     |        |        |          |        |        |        |        |     |          |
| CrptMgt          | 0.0     | 0.0   | 0.1      | 0.0   | -0.1   | 0.0     | 0.0      | 0.1      | 0.1    | 0.0   | 0.1 | 0.1     | -0.1    | 0.1 | 0.1   | 1       |        |          |        |        |        |        |     |          |
| Devictax         | -0.1    | -0.1  | 0.0      | 0.2   | 0.1    | -0.2   | 0.1      | -0.1     | 0.0    | 0.0   | 0.1 | -0.1    | 0.1     | 0.1 | 0.1   | -0.1    | 1     |          |        |        |        |        |     |          |
| SoftPrc          | -0.80   | -0.82 | -0.83    | 0.0   | 0.2    | -0.3   | -0.4     | -0.5     | -0.7   | -0.7  | 0.0  | -0.1   | -0.6    | 0.1  | 0.3   | 0.6     | 0.0    | 0.0    |        |        |        |        |     |          |
| GovPro           | 0.5     | 0.4   | 0.5      | -0.3  | 0.0    | 0.2    | 0.4      | 0.3      | 0.5    | 0.3   | 0.0 | 0.2     | 0.3     | -0.2 | -0.7  | 0.1     | -0.2   | -0.5  | 1       |        |        |        |        |     |          |
| MbbCov           | 0.5     | 0.7   | 0.6      | -0.1  | -0.3   | 0.6     | 0.3      | 0.4      | 0.5    | 0.8   | -0.1 | 0.1     | 0.6     | -0.1 | 0.3   | -0.6    | 0.1    | -0.1  | -0.6    | 0.3   | 1     |        |        |     |          |
| Spectrm          | 0.0     | 0.0   | 0.0      | 0.1   | 0.0    | -0.1   | 0.0      | 0.0      | 0.0    | 0.0   | 0.1 | -0.1    | 0.0     | 0.0  | 0.0   | -0.1    | 0.0    | 0.1   | 0.1     | -0.1  | 1     |        |        |     |          |
| AppFlag          | 0.4     | 0.6   | 0.5      | -0.1  | -0.3   | 0.5     | 0.2      | 0.4      | 0.4    | 0.6   | 0.1 | 0.1     | 0.6     | -0.1 | 0.2   | -0.4    | 0.0    | 0.2   | -0.5    | 0.1   | 0.6   | 0.0    | 1     |     |          |
| Femlabor         | 0.1     | 0.0   | 0.1      | 0.1   | 0.1    | -0.2   | 0.0      | 0.2      | 0.1    | -0.1  | 0.0 | 0.0     | 0.0     | -0.1 | 0.1   | 0.1     | -0.1   | 0.0   | 0.1     | -0.1  | -0.2 | 1       |        |     |          |
Nam, C., Kwon, Y., Kim, S., & Lee, H. (2009). Estimating scale economies of the wireless telecommunications industry using EVA data. *Telecommunications Policy, 33*, 29–40.

Ovington, T., Smith, R., Santamaría, J., & Stammati, L. (2017). The impact of intra-platform competition on broadband penetration. *Telecommunications Policy, 41*(3), 185–196.

Prieger, J. E. (2013). The broadband digital divide & the economic benefits of mobile broadband for rural areas. *Telecommunications Policy, 37*(6–7), 483–502.

Rogers, E. M. (1995). *Diffusion of innovations* (4th ed.). New York: The Free Press.

Rohman, I. K., & Bohlin, E. (2012). Does broadband speed really matter for driving economic growth? Investigating OECD countries. Social Science Research Network. https://doi.org/10.2139/ssrn.2034284.

Silva, S., Badasyan, N., & Busby, M. (2018). Diversity & digital divide: Using the national broadband map to identify the non-adopters of broadband. *Telecommunications Policy, 42*(5), 361–373.

Viard, V. B., & Economides, N. (2014). The effect of content on global Internet adoption & the global “digital divide. *Management Science, 61*(3), 665–687.

Vicente, M. R., & Lopez, A. J. (2011). Assessing the regional digital divide across the European Union-27. *Telecommunications Policy, 35*, 220–237.

Wunnava, P. V., & Leiter, D. B. (2009). Determinants of intercountry Internet diffusion rates. *The American Journal of Economics and Sociology, 68*, 413–426.

Xu, J., Forman, C., & Hu, Y. J. (2018). Battle of the Internet channels: How do mobile & fixed-line qualities drive Internet use? *Information Systems Research, 30*(1), 65–80. https://doi.org/10.1287/isre.2018.0776.

Yates, D. J., Gulati, G. J., & Marabelli, M. (2015). *Determinants of mobile broadband diffusion: A focus on developing countries*. European Conference on Information System. ECIS 2015 Completed Paper 210. Retrieved from http://aisel.aisnet.org/ecis2015_cr/210.

Yates, D. J., Gulati, D. J., & Weiss, J. W. (2013). Understanding the impact of policy, regulation & governance on mobile broadband diffusion. In *46th Hawaii international conference on system sciences from 7th to 10th of June 2013*. https://doi.org/10.1109/HICSS.2013.583.