

Do educational inequalities affect Internet use? An analysis for developed and developing countries

Abstract

This study investigates whether the existence of educational inequalities at the country level affects Internet use. Additionally, we explore the extent to which these impacts depend on countries' economic development levels. We use a logit model and data set of 69 high- and middle-income countries for the period 2005–2015. We find a negative relationship between Internet use and education inequality for the whole sample. The results confirm that, in addition to the level of education and other socioeconomic variables, the distribution of formal education among citizens within a country is also important to explain Internet use. We also obtain that this distribution affects Internet use to a higher extent in middle-income economies in comparison with high-income ones. Unlike the positive influence of educational levels obtained in the academic literature, the existence of within-country educational disparities negatively influences Internet use. This study demonstrates the influence of countries' educational structure in relative terms in explaining Internet use.

Keywords: Internet; education; digital divide; inequality; information and communications technologies (ICT); economic development.

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1. Introduction

The existence of remarkable disparities in access and use of information and communication technologies (ICT), and in the skills needed to adequately use them, generates various types of digital divides at different levels of analysis (individual, households, regions, and countries). These divides can lead to an increase in other social inequalities, deepening social exclusion (Robinson et al., 2015) and negatively affecting countries' economic and social development (Büchi et al., 2016; World Bank, 2016).

The topic of inequalities associated with digital development has captured researchers' interest in disciplines such as economics and sociology. From the economics perspective, the academic literature has analyzed the digital divide at micro, regional, and macro levels, exploring issues such as the measurement of the digital divide and the study of the determinants of ICT penetration and diffusion. As has been shown, sociodemographic and economic factors play a central role in ICT adoption and use. From the sociological approach, researchers have investigated the possible relationship between digital exclusion and other types of inequalities, arguing that digital inequalities are a subset of social ones (Ali, 2020; Van Deursen et al., 2017; Van Dijk & Hacker, 2003; Van Laar et al., 2017). Attention has been paid to digital exclusion, which has been studied by focusing on inequalities in the access and use of ICT (OECD, 2001) between individuals and social groups (first divide) (i.e., Lucendo-Monedero et al., 2019); the unequal acquisition of the

skills needed for ICT use (second divide) (DiMaggio & Hargittai, 2001; Hargittai, 1999; Van Deursen & Van Dijk, 2011; Van Deursen & Van Dijk, 2015a; Van Dijk & Hacker, 2003); and, more recently, disparities in the impacts derived from ICT use (third divide) (Helsper & Van Deursen, 2015; Helsper et al., 2016; Van Deursen et al., 2017; Van Deursen & Van Dijk, 2011; Van Dijk & Hacker, 2003; Van Laar et al., 2017).

Concerning ICT use impacts, the fourth industrial and services revolutions known as Industry 4.0 and Service 4.0, respectively, generate new divides particularly important in the labor markets. Wage inequalities, employment polarization, and differences in workers' demand according to their level of skills characterize this new era. The new wave of technological development driven by computerization, robotics, and telematics deepens this divide (Baldwin, 2016, 2019). ICT adoption and more specifically the effects of robots and automatization in the industrial sector have led to a great divide between low-skilled workers who perform routine and repetitive tasks and high-skilled workers employed in occupations that demand more sophisticated tasks. According to Baldwin (2016), due to these new technological advances, the medium- and high-skilled workers might be negatively affected by the elimination of their jobs or by the offshoring of their tasks in many industrial and services activities. These effects vary greatly across sectors. For example, the impacts in terms of unemployment would affect to a greater extent workers in manufacturing industries that are more open to incorporating robots as well as workers in the service sector, such as in retail and personal services (Acemoglu & Restrepo, 2020).

Within this context, both the literature on ICT adoption and studies on the digital divide have demonstrated the important role played by the level of education and digital and non-digital skills associated with formal and informal education. However, the academic literature at the country level has mainly focused on the impacts of a group of

economic, social, and demographic factors by considering only their absolute levels but not the influence of the inequalities associated with them.

Some previous studies have focused on the effects of technology adoption and use on various types of inequality, including wage (Pupillo et al., 2018) and educational inequalities (Asongu et al., 2019; Zhou et al., 2019). By contrast, only very few have investigated the inverse relationship, that is, the effect of inequalities on technology use. A few researchers have explored the impacts of income inequality on technology use (Hargittai, 1999; Martin & Robinson, 2007; Vincent, 2016; Wunnaba & Leiter, 2009). However, to the best of our knowledge, no studies have investigated the role played by educational inequalities on technology use at the country level. In a moment in which inclusive development is a priority not only for governments in less developed countries but also for the more advanced economies (Paunov, 2013), the study of how educational disparities affect countries' technology use may have important implications for economic development policies. Consequently, in this study we investigate whether educational inequalities affect technology use, in particular, Internet use. We also aim to investigate whether impacts vary according to countries' economic development levels.

It should be noted that by education inequality we refer to the disparities in educational levels, that is, differences in school attainment levels within a country. Education inequality reflects the disparities in opportunities to access the educational system. This is especially relevant for the less advanced economies, where sociocultural and economic factors, together with specific features of the educational system, may condition people's opportunities to access certain educational attainment. By Internet use, we refer to individuals who have used the Internet in the last 12 months, through a fixed or mobile network.

The remainder of the paper is structured as follows. In the next section, we present the conceptual framework of our research. Section 3 is devoted to reviewing the academic literature. Sections 4 and 5 show the research model and data and methodology, respectively, used in our empirical analysis, developed in Section 6. Finally, the main conclusions and the discussion of our results are shown in Section 7.

2. Conceptual framework

The academic literature highlights the importance of technology diffusion as a social process. According to the epidemic models of the diffusion of innovations, technology diffusion takes place when potential users have contact with early adopters (contagion models), when users are influenced by a critical mass within the same social group (social influence), or when people have collected enough evidence and learn from others' experience to be convinced to use technology (social learning) (Young, 2009). The diffusion theory of innovations (Rogers, 2003) states that, in a first stage, users need to gain knowledge about the existence of technology and about how to use it. At this phase, individuals' prior knowledge is critical for technology adoption. In this sense, the user's educational level plays a significant role in technology use. Likewise, heterogeneity models (Rosenberg, 1972) have emphasized that socioeconomic characteristics of users, such as educational level, are important to explain the differences in technology adoption rates (Geroski, 2000; Karshenas & Stoneman, 1995). In this vein, several theoretical models from the economics literature have also demonstrated the importance of human capital to adopt and use new technologies (Benhabib & Spiegel, 2005; Nelson & Phelps, 1966; Rosenberg, 1972). A higher educational level allows individuals to be more open to accepting the risks of using technology. It also favors the skills development needed to use

technology in a more efficient way (Cruz-Jesus et al., 2017; Riddell & Song, 2017). In this context, educational level has been traditionally considered as a significant determinant of Internet use (Bonfadelli, 2002; Robles & Torres-Albero, 2012), as has been recently shown in the literature on the digital divide (Scheerder et al., 2017).

In addition, the existence of educational inequalities may influence the communication flows between individuals, reducing these flows to individuals with similar skills and educational attainment. In developing countries, these inequalities could prevent a critical mass of individuals from reaping the benefits of Internet diffusion on economic growth (Billon et al., 2018). Then, in such countries this situation could restrain investment in education and restrict individuals' opportunity for an education.

The social influence and the pressure of the social network affect individuals' perceptions about technology, thus contributing to reducing the uncertainty associated with its usage (Rogers, 2003). In this sense, technology diffusion as a social process requires the existence of local interactions and interpersonal communication channels to facilitate the transmission of knowledge flows about technology use (Camagni & Capello, 2013; Li et al., 2019). These interactions are affected by the similarities and disparities of individuals' socioeconomic attributes and attitudes (Dutton & Reisdorf, 2019) and by the specific socioeconomic context in which technology use takes place (MacKenzie & Wajcman, 1999; Williams & Edge, 1996). In particular, Rogers (2003) also refers to the importance of considering socioeconomic factors in relative terms, since perceptions about technology may be influenced by the relative position of users within the local system.

The academic literature has also emphasized that several types of proximity, such as cognitive, relational, and social proximities, affect the social learning processes of technology use (Boschma, 2005; Capello, 2009; Jaffe, 1986; Wejnert, 2002). The first

refers to the cognitive similarities of agents and organizations that may favor knowledge diffusion. Social proximity has been defined as social interactions based on friendship, relationship, and experience (Boschma, 2005), whereas relational proximity includes not only the social interactions but also the functional, hierarchical, and economic ones that take place in a specific geographical location, the so-called relational space (Capello, 2009). Conversely, the cognitive, relational, and social distance between users within countries might affect ICT diffusion. In this regard, and although researchers have investigated the influence of educational levels on ICT use, the impacts of the social divide associated with these types of inequalities have barely been explored.

Additionally, both social scientists and economists have paid great attention to the socioeconomic context in which technology use takes place. Social shaping of technology theory (MacKenzie & Wajcman, 1999; Williams & Edge, 1996) states that technology adoption and use are shaped by individuals and society within their specific socioeconomic contexts. Economists have also demonstrated that socioeconomic factors shape technology use and more specifically that of ICT. They have usually explained technology diffusion as the result of supply and demand forces that reflect the economic and social structure and countries' development levels (Comín & Mestieri, 2014; Karshenas & Stoneman, 1995). In this context, countries' educational level has been considered one of the main factors from the demand side.

Despite all of the above, the technology diffusion literature at the country level has mainly focused on the impacts of a group of economic, social, and demographic factors, considering their absolute levels but not inequalities associated with them. Therefore, this literature has ignored the negative influence that these inequalities could potentially have on technology diffusion. In this sense, when analyzing the factors explaining ICT use, the

influence of social divides, such as educational disparities, along with the specific economic and social context, should be considered.

3. Empirical literature review

3.1 Education and ICT use

Several micro-level studies using national surveys have shown the positive relationship between individuals' educational level and Internet use, both in developed countries, such as the Netherlands (Helsper & Van Deursen, 2017; Van Deursen & Van Dijk, 2015b), the US (Azari & Pick, 2005; Pick et al., 2015), Switzerland (Bonfadelli, 2002), Finland (Arief et al., 2018), or Spain (Robles & Torres-Albero, 2012; Serrano-Cinca et al., 2018), and in emerging economies, such as China (Zhu & Chen (2013) and India (Pick et al., 2014).

The empirical evidence, using data at the country level and international statistics, has also shown a positive impact of education on ICT use at the macro level for a set of developed and developing countries (Chinn & Fairlie, 2007; Kottemann & Boyer-Wright, 2009; Wunnava & Leiter, 2009), education being the factor that shows the highest contribution to ICT diffusion (Park et al., 2015; Pick & Nishida, 2015; Vincent, 2016). Other studies focusing on certain geographical areas have also emphasized this positive association. Chong and Micco (2003) among Latin American countries, Ngwenyama et al. (2006) for Africa, Quibria et al. (2003) for Asian countries, and Demoussis and Giannakopoulos (2006) for European countries are some examples.

Some studies have analyzed the ICT adoption process separately according to economic development levels. Some researchers have shown that education seems to be

more relevant to explain ICT adoption in developing countries than in developed ones (Bagchi & Udo, 2007; Kiiski & Pohjola, 2002), while others have found that there are no differences between developing and developed countries (Kottemann & Boyer-Wright, 2009; Pick & Azari, 2008; Pick & Nishida, 2015). Finally, some authors have analyzed the relationship between ICT use and education, taking into account countries' digitalization level. Billon et al. (2010) found that education is only significant to explain ICT usage in middle digitalized countries.

Different arguments have been considered to explain this association between education and ICT usage. According to Pick and Nishida (2015) and Cruz-Jesus et al. (2016), more educated individuals are most likely exposed to ICT usage in their professional and personal lives. Following this argument, some authors have shown differences in the use of the Internet depending on educational levels. People with lower educational levels would have lower ICT access, lower levels of ICT skills, and frequently would use technology, and the Internet in particular, in less beneficial ways (Van Deursen & Van Dijk, 2015a). In this context, Van Dijk (2013) and Van Deursen and Van Dijk (2014) developed the "knowledge gap" theory and deployed the term "education usage gap," arguing that people with lower educational levels spend more free time engaging in social interaction and gaming than for educational purposes, information seeking, or work-related reasons.

Despite the empirical evidence and arguments, only Cruz-Jesus et al. (2016) have partially considered the influence of educational inequalities on ICT use. According to their results, in general, high-educated Europeans show greater use of ICT in comparison with low-educated ones. However, there is no evidence about whether the educational distribution may directly affect Internet use.

3.2 *Economic development and ICT use*

Several authors have provided empirical evidence about the effects of economic variables such as gross domestic product per capita (GDPpc) (see Cruz-Jesus et al., 2017 for a review of studies using GDP to explain the digital divide) on ICT use (i.e., Pick & Nishida, 2015; Vincent, 2016). Researchers have argued that economic wealth is a prerequisite for ICT diffusion and one of the main determinants of disparities in ICT use (Billon et al., 2009).

In the academic literature we mostly can find a positive association between economic development and ICT use, from preliminary studies (i.e., Balamoune-Lutz, 2003; Chinn & Fairlie, 2007, 2010; Dewan et al., 2005; Hargittai, 1999; Kiiski & Pohjola, 2002; Quibria et al., 2003) to more recent papers (Cruz-Jesus et al., 2017; Park et al., 2015; Saidi & Mongi, 2018; Vincent, 2016). For example, Cruz-Jesus et al. (2017) have found that this relationship is not linear and that the association between GDPpc and ICT use is stronger for poorer countries than for rich ones, confirming previous research developed by Billon et al. (2009).

Other authors have considered other variables, such as the service sector as a ratio of GDP, confirming this positive association (Billon et al., 2009; Park et al., 2015). Additionally, other studies have included international trade and foreign direct investment variables to capture countries' level of integration into global markets (Balamoune-Lutz, 2003; Park et al., 2015; Pick & Azari, 2008).

The academic literature has also emphasized the role played by institutional development as a key factor for the diffusion of technology and, in general, for economic development (Acemoglu & Robinson, 2000; Acemoglu et al., 2007; Acemoglu &

Robinson, 2012; Rodriguez-Pose, 2020). Institutional quality is of particular importance to understand differences in economic development levels and in the digital divide between developed and developing countries (Milner, 2006). Poor institutional quality can negatively affect the acceptance of technological change by society in less developed economies. “Good” institutions or so-called inclusive institutions (Acemoglu & Robinson, 2012) can foster technology adoption rates through incentives and other public policies. For example, inclusive institutions positively affect educational policies and citizens’ level of skills when using technology. The institutional framework also affects access to labor markets where digital skills are used. The institutional quality boosts public services such as those associated with telecommunications infrastructure, facilitating access to technology. Inclusive institutions also contribute to networking, lowering information costs, and generating positive externalities that favor knowledge transmission about technology use (Rodriguez-Pose, 2013, Rodriguez-Pose & Zhang, 2020). By contrast, poor institutions, by negatively affecting the supply and demand of technology, can constrain personal interactions and increase transaction costs, having an impact on the perceived benefits and costs of technology use (Milner, 2006; Rodriguez-Pose, 2013).

To sum up, different empirical studies have identified a positive relationship between economic development and ICT use, and between education and ICT use. Nevertheless, the relationship between education and ICT use is not clear and depends on countries’ economic development. Moreover, no studies have considered the role played by educational inequality in ICT use. In this study, we try to address both issues.

4. Research questions and empirical model

We are interested in analyzing the effect of educational inequalities on Internet use. Our specific research question is the following: Do educational inequalities at the country level affect Internet use? Additionally, we aim to determine whether the impacts of educational inequalities on Internet use differ according to economic development levels.

We propose an empirical model that considers educational inequalities and other variables that capture the socioeconomic context to explain Internet adoption at the country level. Our base model is as follows:

$$Internet = f(Edu; Educlneq; GDP; Serv; ICTimports; Cost; Bandwidth; Density) \quad (1)$$

To capture ICT use and as a dependent variable, we have selected the proportion of Internet users (*Internet*) (Bagchi, 2005; Chinn & Fairlie, 2007, Balamoune-Lutz, 2003; Billon et al., 2010; Rodriguez-Crespo & Martínez-Zarzoso, 2019; Vincent, 2016). As explanatory variables, we consider socioeconomic measures to capture the influence of both supply and demand factors affecting Internet use. To measure the educational level (*Edu*) we use the average years of schooling of the population aged 25 years and over. We expect a positive association of this variable with Internet use (Chinn & Fairlie, 2007; Kämpfen & Maurer, 2018; Riddell & Song, 2017). We also include our variable of interest, educational inequality (*Educlneq*), which, following Checchi (2000), is approached by using the Gini coefficient on the school attainment data of the population aged 25 years and over:

$$G^H = \frac{1}{2\bar{H}} \sum_{i=0}^3 \sum_{j=0}^3 |\hat{x}_i - \hat{x}_j| n_i n_j \quad (2)$$

where \bar{H} is the average years of schooling of the population; i and j are the different subgroups considered according to their highest educational level attained (no schooling, primary education, secondary education, higher education); \hat{x}_i and \hat{x}_j are the cumulative average schooling years of each educational level; and n_i and n_j are the shares of the population with educational levels i and j .

We expect a negative association between this variable and the percentage of Internet users. The educational structure and the existence of a less egalitarian distribution of education within a country may affect how knowledge flows associated with technology use are disseminated throughout the social and economic system. In many developing countries, low levels of human capital relate to greater inequalities in the distribution of education (Castelló-Climent, 2010). We expect that in societies with higher levels of educational inequalities and lower levels of human capital, the proportion of Internet users would be lower.

As economic variables, we employ per capita GDP (GDP , in thousands of US\$) and the proportion of employment in services ($Serv$, as a percentage of total employment). We expect a positive association between these variables and Internet use (Balioune-Lutz, 2003; Park et al., 2015). GDP is associated with countries' economic development level. The higher the level of development, the higher the use of the Internet (Cruz-Jesus et al., 2017). As for employment in services, many services, especially knowledge-intensive ones, are associated with higher levels of Internet use (Billon et al., 2009; Park et al., 2015).

Additionally, and considering previous empirical evidence, we have included in the model other variables, such as: a) International Internet bandwidth ($Bandwidth$, in Mbit/s), to measure the expected positive effects of ICT infrastructure (Billon et al., 2010; Chinn &

Fairlie, 2007; Cruz-Jesus et al., 2017; Vincent, 2016; Quibria et al., 2003); b) *Cost*, measured as the fixed broadband Internet monthly subscription, to consider the relevance of ICT prices (Billon et al., 2009; Kiiski & Pohjola, 2002; Vicente & López, 2006); and c) *ICT imports* (percentage of total imports), as a measure to consider the relevance of the country's communication technology size (Vincent, 2016). It should be expected that high levels of ICT imports would be related with higher levels of ICT use, and therefore we would expect a positive effect of access to technology through such imports on Internet use.

Finally, as a variable capturing demographic characteristics, we have selected the population density (*Density*, as people per square km of land area). It might be expected that high population density would promote a low cost of access to the Internet and may favor information and knowledge flows associated with Internet use (Park et al., 2015).

5. Methodology and data

Prior to estimating the proposed empirical model, it is worth commenting on some issues affecting the estimations. The first one relates to the type of random variable that we use as a dependent variable. Given that our interest focuses on explaining the proportion of Internet users, we use a variable that is lower and upper bounded (between 0 and 1). Therefore, a linear regression of this variable on a set of explanatory variables does not ensure that predictions will be bounded between 0 and 1. Instead, the logistic curve is commonly used, as it ensures that predicted values are bounded between 0 and 1 (Papke & Wooldridge, 1996). Thus, p being the proportion of individuals who respond in a given way, the logistic model for p as a function of the explanatory variable x would be:

$$p = \frac{e^{a+bx}}{1+e^{a+bx}} \quad (3)$$

As this model is not linear, we divide this expression by $(1-p)$, i.e., calculate what is known as the odds, and take natural logarithms to obtain a linear model (logit link function):

$$\ln\left(\frac{p}{1-p}\right) = a + bx \quad (4)$$

Therefore, using this transformation to set the empirical model that is estimated in the next section, expression (1) would be:

$$\ln\left(\frac{Internet_{it}}{1-Internet_{it}}\right) = \beta_0 + \beta_1 Edu_{it} + \beta_2 EducIneq_{it} + \beta_3 GDP_{it} + \beta_4 Serv_{it} + \beta_3 ICTimports_{it} + \beta_4 Cost_{it} + \beta_5 Bandwidth_{it} + \beta_6 Density_{it} + u_{it} \quad (5)$$

where i denotes countries, t time, and u_{it} is the error term.

At this point, an option would be to use ordinary least squares (OLS) to estimate the logistic transformation of the model. However, there are at least two reasons for not doing so. On the one hand, the variance of proportions is not constant but depends on the values of p (being lower as p approaches 0 and 1, and being the highest when p equals 0.5). On the other hand, errors do not fit a normal distribution, as is assumed in the linear regression. Instead, it is more appropriate to use a framework of generalized linear models (GLMs) with binomial errors (Crawley, 2013). GLMs are an extension of linear models when their assumptions are not met (Nelder & Wedderburn, 1972). In the context of the present research, GLMs allow us to fit a logit link function with errors that are not normally distributed and do not have a constant variance. Therefore, equation (5) will be estimated assuming that the error term follows a binomial distribution (since the response variable is the proportion of Internet users). As for the logit models, previous studies have also used

them to explain Internet use (i.e., Dobransky & Hargittai, 2016; Martin & Robinson, 2007; Park et al., 2015).

Finally, some precautions need to be taken on the interpretation of the results of the model estimate. The first one has to do with the fact that the global significance of the model is now addressed based on the chi-squared distribution. This approximation is reasonable for large samples but could be poor for small ones. Hence, hypothesis testing is less precise than in the case of normal errors, and therefore caution is needed when interpreting the tests of hypotheses on the parameters. The second precaution concerns the possibility of an overdispersion problem, i.e., variance that is above what is assumed in the model. This could lead to obtaining wrong p -values and, consequently, to declaring statistically significant parameters that are not significantly different from zero. The simplest way to deal with this shortcoming in the estimations is to use a scale parameter that corrects errors to better reflect the actual variance (Crawley, 2013).

As for the data used, our sample consists of a set of 69 high- and middle-income countries for the 2005–2015 period. Our period of analysis has been conditioned by the availability of disaggregated education data needed to estimate the Gini coefficient. GDP data were obtained from the World Bank Database (2019). Data on employment in services are from the International Labour Organization (2019). The proportion of Internet users, fixed broadband Internet monthly subscription costs, and international Internet bandwidth are from the International Telecommunications Union (ITU, 2019). Finally, data on years of schooling are from the Barro and Lee Data Set (2013) and UNESCO Institute for Statistics (2019). Table 1 summarizes the descriptive statistics of the variables. As can be seen, on average 52.9% of the population use the Internet in our period of analysis. There

are important differences between countries, with the percentage ranging widely from 3.6% to 96.3%. The average proportion of Internet use in high-income countries is 68.5%.

[Table 1]

6. Results

6.1. A first approach to the relationship between education inequality and Internet use

Prior to the estimation of our empirical model, we found it interesting to perform an analysis of the relationship between the two social variables of interest. In particular, we aimed to investigate whether educational inequality differs in its relationship with Internet use for developed and developing countries.

Figure 1 shows the relationship between the two variables for the whole set of countries, without making distinctions between middle- and high-income countries. We observe a negative relationship between education inequality and Internet use, the countries with greater inequality being those that exhibit a lower level of Internet diffusion. The correlation between both variables is -0.551 and significant, reinforcing the idea of an inverse relationship between these two variables. The regression line plotted on the graph shows a negative slope, i.e., the higher the educational inequality the lower the Internet use.

[Figure 1]

To obtain a better picture of the relationship between Internet use and educational inequality, in Figure 2 we present the evolution of this relationship over the 2005–2015 period. Countries have been classified according to their level of educational inequality (value of the Gini coefficient). Thus, countries with low levels of educational inequality are

those in the first quartile, whereas economies with high levels of educational inequality are those in the fourth quartile. As can be observed, Internet use is lower for countries with a high level of educational inequality, and this fact is registered for the whole period.

[Figure 2]

Additionally, educational inequality is closely linked to the countries' economic development. It would be reasonable to think that inequality will be greater in low-income countries since their access to education is more restricted than in high-income ones. The average value of the Gini coefficient is 11.92 for high-income countries and 24.78 for middle-income countries. Figure 3 shows the distribution of educational inequality for high-income and middle-income countries. This box-and-whisker plot shows two facts. First, as expected, educational inequality is higher in middle-income countries than in high-income ones. Second, dispersion is also higher for middle-income countries, especially for countries with lower levels of educational inequality.

[Figure 3]

6.2 Model estimation

In the previous section, we showed that there are differences in the levels of educational inequality according to countries' economic development levels. In this section, we present the results of our multivariate analysis. In Table 2, first, we show the results of the estimation of the base model (4) for the whole sample in column (A). Then, in column (B) we present the results considering countries' economic development level.

According to the results presented in column (A), almost all the variables show a significant role in explaining Internet use. Therefore, we observe that variables capturing economic development characteristics are relevant to explain a greater use of the Internet,

confirming the previous empirical evidence. As for the education variables, the results indicate that both educational level and educational inequalities are significant and display the expected signs. We find a positive coefficient associated with the average years of schooling, confirming previous empirical evidence (Chinn & Fairlie, 2007; Kämpfen & Maurer, 2018), while the coefficient associated with education inequality is negative. Therefore, this provides evidence in favor of the positive contribution of the educational attainment of the population in a country to explain Internet use, in line with previous studies mentioned in Section 3, “Empirical literature review.”

[Table 2]

In addition to the previous finding, the negative and significant coefficient of educational inequality shows, for the first time, that the distribution of formal education among citizens in a country is also important to explain Internet use. It is not only that the level of education affects Internet diffusion, but also that educational inequalities matter for Internet use when we consider a long period and a large number of countries.

Regarding the variables that approach the economic development level, the results point to their positive contribution to Internet use. Thus, the coefficients of per capita GDP and the percentage of employment in services are both positive and significant, in line with the available academic literature.

If we draw our attention to variables directly related to ICT infrastructure, bandwidth shows the expected positive sign, confirming that it is a key variable in explaining Internet use. The better the infrastructure, the higher the navigation speed, and the more likely the use of the Internet. This positive relationship has been previously found by Quibria et al. (2003), Chinn and Fairlie (2007), and Vincent (2016), among others. However, it seems that connection costs have no impact on Internet use, confirming previous empirical

evidence (Billon et al., 2010; Chinn & Fairlie, 2007; Hargittai, 1999) and reiterating the need to develop new studies to obtain conclusive results about this relationship. As for ICT imports, the coefficient is positive and statistically significant, indicating that positive access to ICT through imports affects Internet use. Finally, to check if some of the explanatory variables (particularly income and education variables) could be correlated, we have calculated the variance inflation factors (VIFs) to test for the presence of multicollinearity. The results indicate that no multicollinearity problems are affecting our estimates, since the highest VIF was for educational level (3.88), followed by per capita GDP (3.34), with the remaining VIFs being below 2.5.

As we showed in Section 5, “Methodology and data,” educational inequality differs between high- and middle-income countries. In this section, we are interested in testing whether this difference has any effect on our results. For that purpose, we created a dummy variable that identifies high-income countries (*high*). The interaction of this dummy with the educational inequality variable allows us to detect the existence of differences in the coefficient obtained in column (A) for high-income countries. The results of the estimation are displayed in column (B) – Table 2-. The fact that we obtain a positive and significant coefficient for this new term suggests that educational inequality is less important in explaining Internet use in high-income countries than in middle-income ones. Moreover, this positive coefficient means that the obtained negative coefficient for the educational inequality variable should be corrected by adding the value of this new coefficient in the case of high-income countries. Because both coefficients are similar in magnitude and with an opposite sign, the result can be interpreted as a nil contribution of educational inequality to explain Internet use in the case of high-income countries.

This result points to the different relevance of the impacts of educational inequalities on Internet penetration depending on countries' economic development levels. This outcome may indicate that the effects of educational inequalities on technology diffusion also depend on a variety of factors that appear to be associated with countries' specific economic and social context.

As an additional analysis, we have added a column (C) that presents an alternative specification in which those variables that could potentially cause endogeneity problems have been lagged one period.¹ The results in column (C) are very similar to those in column (B), pointing out that there appears to be no bias in our parameter estimates.

Moreover, as our results emphasize the importance of other factors associated with countries' specific features, we have also included a new column (D) to illustrate the role played by institutional quality in the diffusion of Internet use. To measure institutional quality we used the regulatory quality estimate of the World Bank (*Regqual*). This indicator captures the ability of the government to permit and promote private-sector development through policies and regulations. Previous empirical evidence has shown a positive impact of this variable to explain Internet diffusion (Billon et al., 2009, 2010; Chinn & Fairlie, 2007; Zhao et al., 2007). As expected, the results provide evidence of the positive impact that institutional quality has on Internet use. Finally, we also aim to explore if this effect differs between high- and middle-income countries. To that end, we added a variable that results from the interaction between regulatory quality and a dummy that identifies middle-income countries (*Regqual*mid*). The estimates (column E) point to a lower impact of institutional quality for middle-income countries, as we obtain a negative coefficient for

¹ It is assumed that in case it exists, simultaneity would be the source of endogeneity (Martin & Robinson, 2007).

this interaction term. The result is in line with the fact that developing countries have poorer institutional quality in comparison with high-income economies and confirms previous empirical evidence (Billon et al., 2009, 2010).

7. Conclusions and discussion

This paper analyzed whether educational inequalities explain Internet use in the period 2005–2015 for a set of 69 countries. Our results imply that the distribution of formal education among citizens in a country is important in explaining Internet adoption. It is not only that the level of education affects Internet diffusion, but also that educational inequalities matter for Internet use when we consider a long period and a large number of countries. Unlike the positive influence of educational levels, the existence of within-country educational inequalities negatively influences Internet use. Moreover, our findings show that the relevance of educational disparities on Internet penetration varies depending on countries' socioeconomic development levels. Among high-income countries, the impact of educational inequalities on Internet use seems to be practically nil, while for middle-income countries its impact is significant and negative.

Our results also imply that the design of public policies to improve the diffusion of ICTs should consider not only supply-and-demand factors in absolute terms, as explored in the economic literature, but also the role played by educational inequalities in ICT penetration and diffusion. Additionally, our findings indicate the need to consider the specific characteristics of each country, the relationships between economic and social factors, and the influence of countries' social structure in relative terms, as elements that explain how societies shape technology.

In this context, it would be advisable to put into practice actions that would facilitate populations in gaining access to the highest possible educational attainment. This would reduce the gap between those individuals enjoying high educational levels and those who do not. Reduction of educational inequalities could have positive effects on Internet diffusion, in particular among countries with lower economic development levels.

Educational policies devoted to increasing educational levels and reducing educational disparities among the less developed countries could involve the implementation of different strategies, such as increasing the years of compulsory schooling, given the positive effects of early-life education on Internet use (Kämpfen & Maurer, 2018). At the same time, an increase in Internet diffusion could have a positive effect on primary education (Asongu & Odhiambo, 2019), contributing to reducing educational inequalities in less developed countries. Promotion of gender parity in educational programs, following the recent experience registered in some African countries (Asongu et al., 2019), would be another possible educational strategy. Special emphasis should be put on improving ICT physical infrastructure and the quality of digital educational resources, contributing to reducing the lag between urban and rural schools (Wu et al., 2019). An increase in ICT diffusion in rural schools may reduce educational inequalities in less developed countries, to help create what Dutton and Reisdorf (2019: 19) call the “Internet culture” (defined as “patterns of beliefs and attitudes concerning the Internet”) in rural areas where Internet diffusion is small, contributing to shaping digital divides, and consequently, also educational inequalities.

In this context, further research should explore the impacts of educational inequalities and other social forms of exclusion on specific measurements of the digital divide at the country and regional levels. This might contribute to our understanding of the relationships

between several manifestations of social and digital divides in a moment in which inclusive development is a policy issue for many governments in the globalization era. In this vein, the impacts of the new digital technologies open up new areas for further research. As mentioned earlier, initially advanced manufacturing and information and communication technologies have reduced the demand for labor in a wide range of manufacturing tasks developed by blue-collar workers. In the future, automatization, robots, and artificial intelligence (AI) are expected to reduce the demand for labor in a wide range of tasks developed by white-collar workers in many services and professional jobs (Baldwin, 2019). This effect might be counterbalanced by the simultaneous creation of many new tasks (Acemoglu & Restrepo, 2019). However, this “globoitics transformation,” as Baldwin (2019) has coined it, would require a reorientation of skills development toward those without direct competition with robots and AI (i.e., flexibility, adaptability, face-to-face contact with other people) (Baldwin, 2019). This new situation would have unexpected implications for social, economic, and educational inequalities, and it would require further research.

As one of the main limitations of our study, we should highlight the difficulties in obtaining disaggregated education data, especially for middle- and low-income countries. The availability of these types of data would have allowed us to calculate comparable inequality measures between countries and increase the number of countries in the sample.

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Table 1. Summary statistics

	mean	std.dev.	minimum	maximum
<i>Internet_{it}</i>	0.529	0.242	0.036	0.963
<i>Edu_{it}</i>	9.897	2.256	4.3	13.8
<i>EducIneq_{it}</i>	14.687	9.222	0.693	58.280
<i>GDP_{it}</i>	22.552	18.193	1.041	89.080
<i>Serv_{it}</i>	64.605	11.732	33.7	87.0
<i>ICTimports_{it}</i>	5.075	10.723	0.520	72.387
<i>Cost_{it}</i>	26.176	11.208	5.281	81.884
<i>Bandwidth_{it}</i>	11.830	23.634	0.0001	210.0
<i>Density_{it}</i>	652.773	2138.841	2.766	18283.679

Note: Authors' own calculations.

Table 2. Estimation results

	(A)	(B)	(C)	(D)	(E)
<i>Intercept</i>	-2.3370*** (0.3107)	-2.3048*** (0.3054)	-2.4339*** (0.3091)	-1.9069*** (0.3170)	-1.8813*** (0.3158)
<i>Edu_{it}</i>	0.0681*** (0.0260)	0.0734*** (0.0255)		0.0468* (0.0259)	0.0137 (0.0295)
<i>Edu_{it-1}</i>			0.0749*** (0.0251)		
<i>EducIneq_{it}</i>	-0.0137*** (0.0049)	-0.0136*** (0.0049)	-0.0138*** (0.0049)	-0.0140*** (0.0048)	-0.0148*** (0.0047)
<i>GDP_{it}</i>	0.0245*** (0.0036)	0.0181*** (0.0039)		0.0113*** (0.0043)	0.0042 (0.0052)
<i>GDP_{it-1}</i>			0.0158** (0.0039)		
<i>Serv_{it}</i>	0.0157*** (0.0040)	0.0138*** (0.0040)		0.0121*** (0.0039)	0.0175*** (0.0045)
<i>Serv_{it-1}</i>			0.0163*** (0.0037)		
<i>ICTimports_{it}</i>	0.0202* (0.0105)	0.0235** (0.0108)		0.0157 (0.0104)	0.0161 (0.0106)
<i>ICTimports_{it-1}</i>			0.0257** (0.0113)		
<i>Cost_{it}</i>	-0.0016 (0.0029)	-0.0009 (0.0028)	0.00002 (0.0028)	-0.0018 (0.0030)	-0.0022 (0.0028)
<i>Bandwidth_{it}</i>	0.1927*** (0.0222)	0.2108*** (0.0225)	0.2064*** (0.0225)	0.2057*** (0.0219)	0.2046*** (0.0218)
<i>Density_{it}</i>	-0.0001 (0.0001)	-0.0001* (0.0001)	-0.0002* (0.0001)	-0.0001 (0.0001)	-0.0001 (0.0001)
<i>EducIneq_{it} * high</i>		0.0240*** (0.0070)	0.0257*** (0.0069)	0.0183*** (0.0069)	0.0121* (0.0074)
<i>Regqual_{it}</i>				0.3223*** (0.0897)	0.5819*** (0.1427)
<i>Regqual_{it} * mid</i>					-0.3986** (0.1713)
Pseudo R ²	0.859	0.864	0.865	0.869	0.871

*, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Estimations performed using a scale parameter to correct for overdispersion of the model.

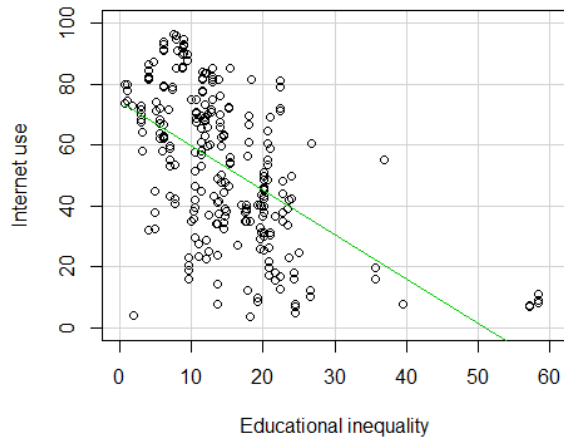


Figure 1. Relationship between Internet use and educational inequality.

Source: Own elaboration with data from ITU (2019), Barro and Lee (2013), and UNESCO (2019).

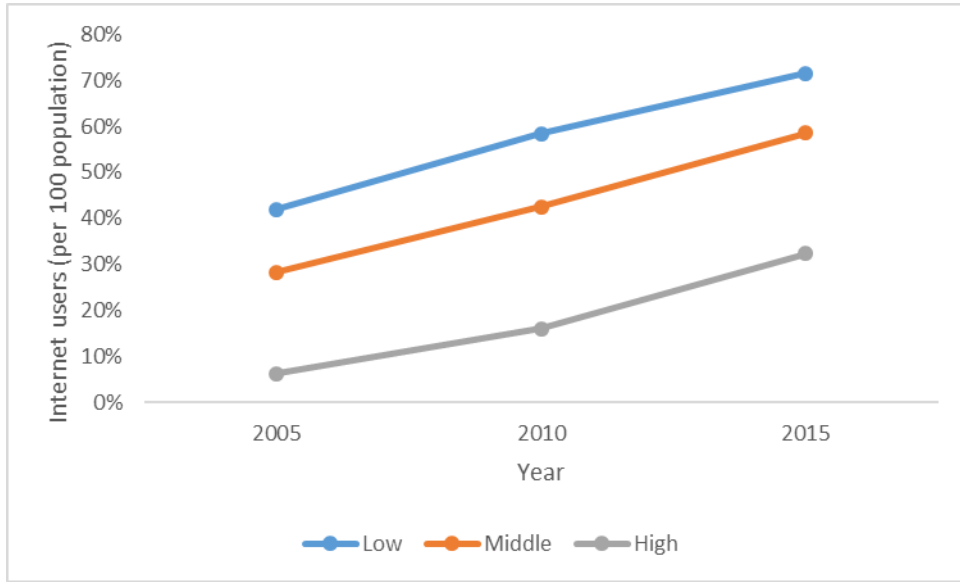


Figure 2. Average diffusion of Internet use by educational inequality level.

Source: Own elaboration with data from ITU (2019), Barro and Lee (2013), and UNESCO (2019).

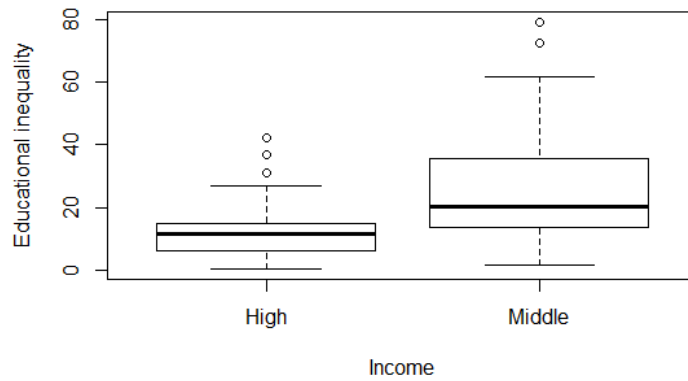


Figure 3. Educational inequality distribution for middle-income and high-income countries. Source: Own elaboration with data from ITU (2019), Barro and Lee (2013), and UNESCO (2019).