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The diffusion of the Internet: A cross-country analysis

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ABSTRACT

This paper analyzes the process of Internet diffusion across the world using a panel of 214 countries during the period 1990–2004. Countries are classified as low- or high-income and it is shown that the diffusion process is characterized by a different S-shaped curve in each group. The estimated diffusion curves provide evidence of very slow "catching up". The paper also explores the determinants of Internet diffusion and shows that network effects are crucial to explain this process. One important finding is that the degree of competition in the provision of the Internet contributes positively to its diffusion.

1. Introduction

The process of technological adoption and diffusion has been extensively studied in the literature.[1] A casual look at data on the diffusion of different technologies reveals that, at a given point in time, there are significant differences in the degree of diffusion or adoption across countries.[2] This paper studies these differences for one technology in particular: the Internet. Understanding the process of Internet adoption and diffusion as well as the main determinants of cross-country differences in this process seems to be of particular interest since, as it has long been acknowledged, the Internet is a key tool of economic development (Kenny, 2003; Röller & Waverman, 2001; Sánchez-Robles, 1998).

Fig. 1 illustrates the significant disparity in Internet diffusion in five countries during the period 1990–2004. Although the number of Internet users per capita was very low in the United States in 1990 (0.8%), the use of this technology increased to 22% in 1997, and jumped to 63% by 2004. France had a low adoption rate for most of the time interval covered here, but this rate grew very rapidly, especially after the year 2000, reaching 39% in the year 2004. These accelerations were clearly not observed in the three other countries of Fig. 1. Brazil had a modest rate of 12% by the end of the period. In China, although Internet use grew very rapidly—from a level of 0.03% in 1997 to 7.2% in 2004, the penetration rate was still remarkably low in that year. Finally, Internet adoption in Tanzania was virtually zero in 1997 and it increased to only 0.9% by 2004. The observed difference in the levels of Internet adoption across countries raises important policy questions.

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[1] See for instance Keller (2001), Comín and Hobijn (2004), Caselli and Coleman (2001), Comín et al. (2006), Barro and Sala-i-Martin (1997), and Jovanovic and Lach (1989).

[2] Chinn and Fairlie (2007) show that, in the year 1993, many developing countries had computer and Internet penetration rates that were 1/100th of the rates found in North American and Europe.

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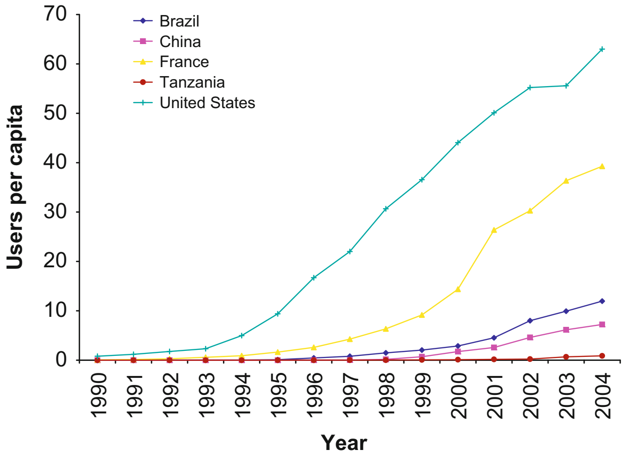

Fig. 1. Internet diffusion in different countries.

Of particular interest to policymakers in developing countries is the need to understand the process of diffusion in order to anticipate if their countries will eventually catch up and close the digital divide and, more generally, to implement the right policies to increase the speed of Internet adoption.

This paper makes use of a comprehensive dataset to study the process of Internet diffusion in a large set of countries for the period 1990–2004. The analysis includes both developed and developing countries and provides separate results for distinct income levels. The paper is broken down to two parts. The first confirms previous studies by showing that the process of Internet diffusion across the world is well described by an S-shape pattern. An important advantage of the dataset used in this exercise that distinguishes it from many previous papers is that it includes data for the initial years in which Internet was adopted and hence it facilitates the estimation of a complete S-shape curve. These curves are estimated for different groups of countries and it is found that low-income countries have a much steeper adoption profile and their curve lies to the right of that of high-income countries. This finding provides support to the hypothesis that Internet adoption follows a leader–follower model whereby low-income countries, as followers, have lower adoption costs.[3]

The second part of the paper identifies variables that explain the differences in cross-country patterns of Internet diffusion. The most innovative finding is the presence of significant network effects in Internet diffusion: the number of Internet users (in a given country) in the previous year is a powerful determinant of the number of Internet users in the current year. The presence of network effects as a determinant of Internet adoption has been largely ignored in existing literature[4]—a striking fact considering that the utility derived from Internet consumption is clearly affected by the number of people using it (Shy, 2001). In addition, this paper studies one determinant that has not been much explored in the literature: the competition in the market for the provision of Internet services. Controlling for different relevant variables, the results suggest that in countries where there is more competition in the distribution of Internet, the number of users increases more rapidly.

The remainder of this paper is organized as follows. Section 2 briefly summarizes the existing literature on technology diffusion and, in particular, on Internet diffusion. Section 3 describes the main dataset used throughout the paper. The empirical estimation of Internet diffusion curves is presented in Section 4. Section 5 explores the determinants of Internet diffusion across countries. Finally, Section 6 offers concluding remarks.

2. Related literature

There exists a vast literature exploring the process of technology diffusion across countries. Since the emphasis of the present paper is empirical, the following summary will omit most of the theoretical analysis.[5]

The majority of the empirical papers on technological diffusion focus on identifying variables that can explain some features of the diffusion process of different technologies. For instance, Gort and Klepper (1982) trace the history of diffusion for 46 new products and correlate it with several economic indicators. Caselli and Coleman (2001) analyze the case of personal computer adoption and provide a comprehensive cross-country analysis that attempts to identify its main

[3] This hypothesis is developed in Chong and Micco (2003).

[4] Estache et al. (2002) is an exception as these authors include a lagged variable of Internet users but find it not significant as a determinant of Internet adoption.

[5] A summary of the theoretical literature can be found in Keller (2001). His review argues that "technology" has been mostly modeled as "technological knowledge". The main theories belong to two groups. The first one (endogenous technological change) views technological change as the outcome of intentional private actions (Aghion & Howitt, 1992; Grossman & Helpman, 1991; Romer, 1990; Segerstrom, Anant, & Dinopoulos, 1990). The other group of theories models technological change as a pool of available resources to the entire world (Mankiw, 1995; Parente & Prescott, 2000).

determinants. Finally, Pohjola (2003) studies observed investment in information and communication technology in 49 countries during the period 1993–2000.

Furthermore, there are plenty of empirical studies on the determinants of Internet usage.[6] Chinn and Fairlie (2007) use panel data from 161 countries for the years 1999–2001 to identify the determinants of cross-country disparities in the usage of personal computers and the Internet. Although income differences play a major role in explaining the digital divide, they show that there are other important determinants such as regulatory quality and the level of infrastructure. Estache, Manacorda, and Valletti (2002) also analyze the determinants of differences in Internet usage across countries and use their results to provide some policy recommendations for the Latin America region. Chong and Micco (2003) study the spread of the Internet in Latin America and argue that, in spite of being latecomers, Latin American countries have the advantage of lower costs of adoption and could easily catch up with technological leaders. They also find that a country's capacity to innovate helps explain the extent to which the Internet is adopted. In a similar framework, Beilock and Dimitrova (2003) find that per capita income is one of the most important factors behind these differences. Their results also suggest that this effect is nonlinear, with income differences having a larger effect in the use of the Internet at lower income levels. Finally, Guillén and Suárez (2001,2005) focus on the effect of economic, political, and sociological factors on Internet usage.

On the other hand, several authors have studied the fact that technology diffusion follows an S-shaped pattern. This empirical recurrence is documented by Griliches (1957), Davies (1979), Gort and Klepper (1982), and Mansfield (1961), and is theoretically modeled in Jovanovic and Lach (1989) among others. More recently, Comín and Hobijn (2004) and Comín, Hobijn, and Rovito (2006) study the diffusion processes of several technologies in different countries over the last 200 years. They find that, once the intensive margin of technological diffusion is accounted for, the evolution of the level of technology in a country typically departs from an S-shaped pattern.

Finally, another strand of the literature has analyzed the positive effect of technology adoption and, in particular, the adoption of Internet on the growth performance of a country and on the digital divide across countries—the gap in access to information technologies between developed and developing countries. Some interesting studies along these lines are Röller and Waverman (2001), Gramlich (1994), World Bank (1994), Sánchez-Robles (1998), Norris (2000), OECD (2001), and Kiiski and Pohjola (2002).

This paper is intended to fill several gaps present in the literature. First, data are used that include the initial years of Internet adoption, thus facilitating the estimation of complete S-shape curves. Moreover, by including both developed and developing countries, it is possible to explicitly analyze differences between countries with differing income levels. The paper also studies the effect that competition and network externalities have on Internet adoption—two factors that have thus far been neglected in most previous studies.

3. The data

Technological diffusion is defined in Gort and Klepper (1982) as "the spread in the number of producers engaged in manufacturing a new product." Given the nature of the Internet, the paper adapts the definition whereby diffusion refers to the number of consumers of the Internet. Although one could think of many indicators of Internet diffusion,[7] the two most widely used are the number (absolute and in per capita terms) of Internet users and that of Internet subscribers.[8] Tables A1 and A2 in Appendix A present descriptive statistics for the total and per capita number of Internet users. Conceptually, Internet users and subscribers are different variables since the former include intra-household access to the Internet as well as people who access the Internet in public places (universities, libraries, cafes). The results using both measures of Internet diffusion are qualitatively similar. Hence, in what follows, only results for Internet users are reported.

The main dataset used in this paper is from the International Telecommunication Union (2006). This dataset contains information on 214 countries for the period 1990–2004.[9] By including both developed and developing countries in the sample, the importance of problems of sample selection raised by De Long (1988) in the context of the literature on growth convergence is taken into account.[10]

[6] No attempt to provide a comprehensive account of these papers is made here. An incomplete list includes Canning (1999), Klobas and Clyde (1998), Kiiski and Pohjola (2002), Quibria, Ahmed, Tschang, and Reyes-Macasaquit (2002), Liu and San (2006), Zhao, Kim, Suh, and Du (2007)), and Leiter and Wunnava (2009).

[7] Press (2000) provides a long list of such indicators: connectivity, host count, number of web sites, language distribution, compound indices of pervasiveness, geographic dispersion, sectoral absorption, connectivity infrastructure, organizational infrastructure, and sophistication of use.

[8] Ideally, one would also like to have measures of the quality and the intensive use of the Internet but this information is not available for a large enough group of countries. It is well- known that developing countries might have a very slow connection to the Internet. For example, in the spring of 1999, Cuba's total international bandwidth was 832 kb/s, which is much less than that in a home with high-speed DSL service or cable modem. Furthermore, connectivity was concentrated in Havana and limited to a relatively few people, almost exclusively through their work (see Martínez, 1999). The picture is much worse in many African countries (see Jensen, 2009).

[9] Zeros are replaced by missing values if a country has had positive figures for a large number of years preceding the missing value. On the other hand, initial missing values are replaced by zeros. The rationale for the latter is that, in most cases, the initial values are quite small, suggesting that initial missing values correspond indeed to zeros.

[10] In order to control for outliers, in all specifications below the observations that correspond to countries with GDP growth above 9.2% or below −4.9% (which represent three standard deviations away from the mean GDP growth) are dropped from the dataset. As a robustness check the regressions

One important aspect of note is that, for most technologies, the relevant measure of diffusion is the ratio of *actual* to *potential* users. Measuring potential users is problematic since it requires access to micro data, which is unavailable for most of the countries in the sample. However, as noted by Dasgupta, Lall, and Wheeler (2001), in the case of the Internet, human capital requirements to use its basic applications (electronic mail and information search) are relatively low. Therefore, it seems reasonable to assume, as the paper does, that the entire user populations are potential users. Hence, the definition used here for the number of Internet users per capita is simply the ratio of users in a country to its total population.

Finally, the paper uses the *World Bank Country Classification* to study potential differences in diffusion patterns across countries with different income levels. The World Bank classifies countries in the year 2005 into four different groups according to their GNI per capita. These groups are *low-income*, *lower-middle-income*, *upper-middle-income*, and *high-income* economies.[11] A list of countries included in each group is shown in Appendix A. The paper follows the World Bank classification, but has opted to group countries into two categories: (i) low-income and lower-middle-income countries, and (ii) upper-middle-income and high-income countries, redefined as "low-income" and "high-income" respectively. This grouping provides more degrees of freedom for the estimations.

4. An estimation of the diffusion process of Internet

As noted in Jovanovic and Lach (1989), there exists strong empirical evidence to support the view that the diffusion path of both new processes and product innovations follows an S-shaped or logistic pattern.[12]

This paper presents two contributions to this stylized fact. First, the hypothesis that Internet diffusion follows an S-shape curve for low- and high-income groups of countries is estimated. There are theoretically sound reasons to believe that the diffusion process of a given technology should be significantly different for poor and rich countries (see Barro & Sala-i-Martín, 1997).

Second, a comprehensive dataset is used, which allows the study of the diffusion process of the Internet since the initial years in which it started to spread in the leading country—the US. This clearly overcomes the selection problem present in most of the existing studies. As acknowledged in Comín and Hobijn (2004), most of these papers lack data for the initial years in which the innovation (or new product) was adopted.[13] This translates into important differences in the estimation of diffusion. In particular, it is shown that the omission of the initial years leads to S-shape curves that grow "too fast" during the early introductory phase.

Fig. 2 plots the actual number of Internet users per capita in the two income groups. It is clear from this graph that, at any point in time, the degree of Internet adoption is much lower in less developed economies than in more developed ones. The use of the Internet in low-income countries did not commence until 1994, whereas it had already occurred in several high-income countries by 1990. In 2004, about 40% of the population of high-income countries enjoyed Internet services, while the percentage was less than 3% in low-income countries. In other words, the diffusion curve for low-income countries can be roughly described as a right shift of the one displayed by high-income countries. This stylized fact seems to support the leader–follower model presented by Chong and Micco (2003).

In order to estimate the diffusion process of the Internet a logistic function is used. This functional form has often been used to approximate the S-shaped diffusion process due to its relative simplicity.[14] The expression for the logistic function used in the estimations is

$$Y_{it} = \frac{\delta_0}{1+e^{-(\delta_1+\delta_2 t)}} + \varepsilon_{it} \tag{1}$$

where Y_{it} represents the number of Internet users per capita in country i at period t and ε_{it} is a white noise.[15] The parameter δ_0 reflects the long-run level of diffusion, that is, the limit of Y_{it} when t goes to infinity; δ_1 is a constant of integration that positions the curve on the time scale and δ_2 reflects the speed of adoption. Eq. (1) is estimated using a nonlinear least squares procedure.

The results of the estimation are displayed in Table 1. The first column presents the estimates for the entire world. Columns 2 and 3 show the estimates for low- and high-income countries, respectively. First, the long run level of diffusion is much higher in high-income countries. Second, the parameter of the speed of adoption (δ_2) is higher for low-income

(*footnote continued*)
are also run using the whole sample. The estimates of those regressions are similar to the ones presented in the main text and are available from the authors upon request.

[11] The income thresholds are: low income, \$875 or less; lower middle income, \$876–\$3,465; upper middle income, \$3,466–\$10,725; and high income, \$10,726 or more.

[12] Kotler (1986) interpreted this fact as evidence in favor of the existence of four phases for technology adoption: introduction, growth, maturity, and decline.

[13] This lack of data is due to the fact that, in most cases, information on the use of a given new technology starts to be collected only after it has been widely adopted. Comín and Hobijn (2004) mention the example of the telephone, which was invented by Alexander Graham Bell in 1876 but most countries did not publish official statistics on its diffusion until the early years of the 1900s.

[14] Other S-shaped functions used include the cumulative normal and the Gompertz model.

[15] Estimations using the total number of users as a dependent variable yield qualitatively similar results.

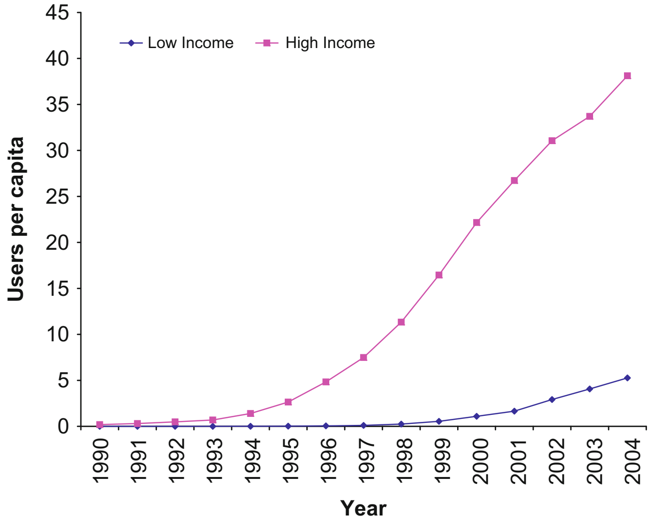

Fig. 2. Internet diffusion in low- and high-income countries.

Table 1
Estimates of the S-shape function using Internet users.

	Entire world	Low income countries	High income countries
δ_0	16.24*** (0.7)	7.28*** (0.27)	41.03*** (1.58)
δ_1	−5.82*** (0.11)	−9.53*** (0.32)	−5.77 (0.13)
δ_2	0.48*** (0.02)	0.7*** (0.03)	0.53*** (0.02)
Method of estimation	NLLS	NLLS	NLLS
Number of observations	15	15	15
R^2	0.99	0.99	0.99

The dependent variable is the number of Internet users per capita. Standard errors in parentheses; *,**, and *** denote significance at the 10%, 5%, and 1% level, respectively.

countries than for high-income countries. This difference suggests that low-income countries have a higher adoption speed, which is consistent with the hypothesis that low-income countries are "catching up", and that followers tend to adopt technologies faster than leaders.

Fig. 3 displays actual and predicted number of Internet users per capita in the world during the years 1990–2004, while Figs. 4 and 5 display the same variables for low-income and high-income countries, respectively. The first thing to notice is that the data and the model display a very clear S-shape pattern, particularly for high-income countries. While the diffusion of Internet is very slow in the initial years it speeds up in the middle years, and then finally slows down. As mentioned above, the fact that the dataset contains information from the very first years of Internet diffusion helps explain why a complete S-shape curve is obtained while most of the related literatures do not. Figs. 4 and 5 show that in low-income countries, diffusion of the Internet accelerates in the last years of the sample, while in high-income countries the process significantly flattens out. This graphical evidence also suggests that low-income countries are at a prior stage of the diffusion process and should eventually catch up with high-income countries in the diffusion of the Internet.

A striking result of Table 1 is the estimate of δ_0, which suggests a lack of long term convergence in Internet diffusion between low- and high-income countries. High-income countries converge to an adoption rate of 41.03%, whereas low-income ones reach a much lower adoption rate of 7.28% in the long run. Provided that the estimation indicates that low-income countries are catching up as their speed of adoption is higher, a relevant question is—in this scenario, how many years would it take for low-income countries to reach the long-term adoption rate of high-income countries? To answer this Eq. (1) is estimated imposing the restriction that the δ_0 coefficient for low-income countries equals 41.03, the estimated long run adoption rate of high-income countries. The result of this counterfactual experiment is shown in Fig. 6. According to the estimates, low-income countries would take 14 years to reach a penetration rate of 40% (in year

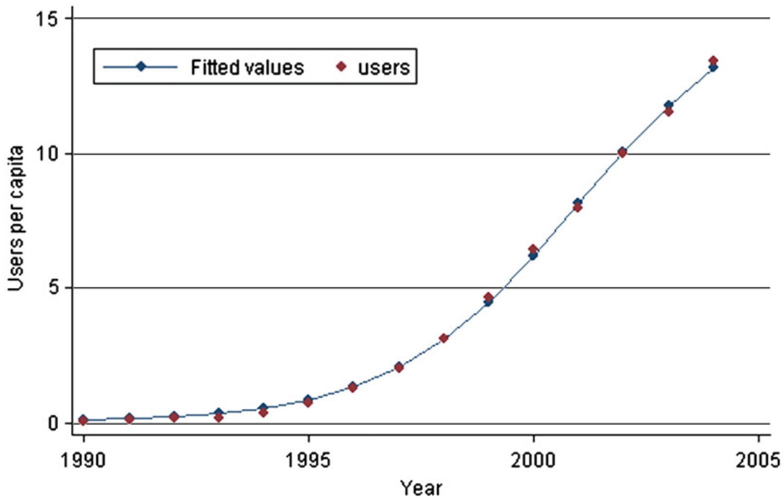

Fig. 3. Internet diffusion in the world.

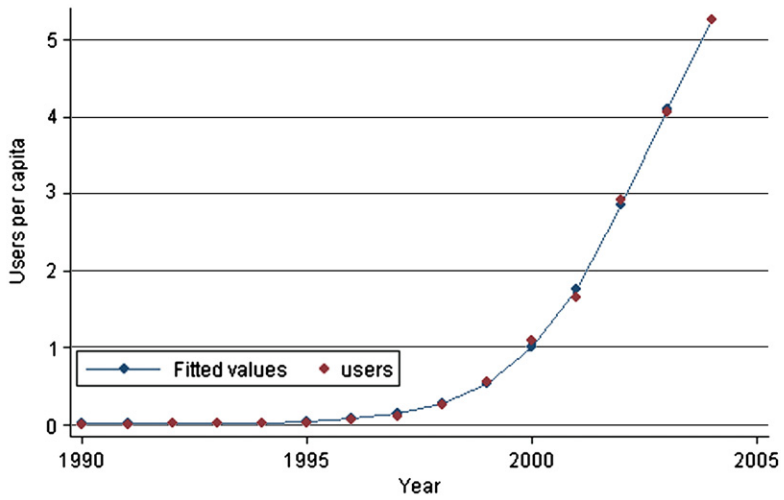

Fig. 4. Internet diffusion in low-income countries.

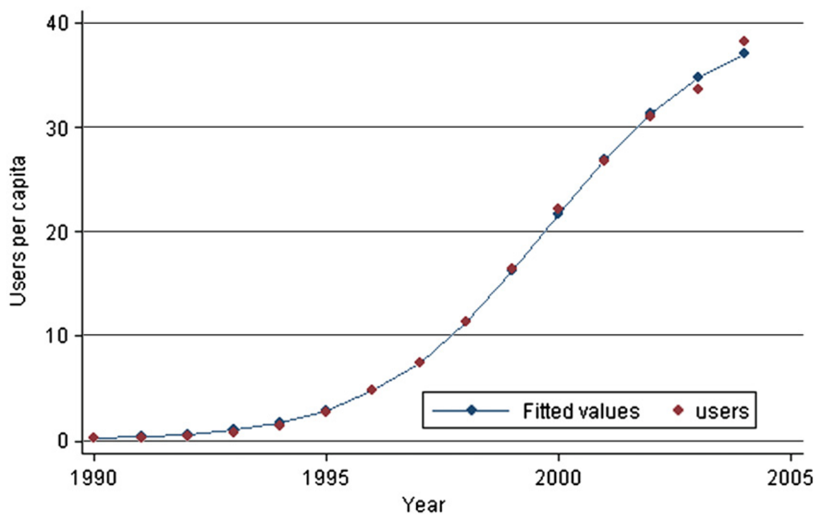

Fig. 5. Internet diffusion in high-income countries.

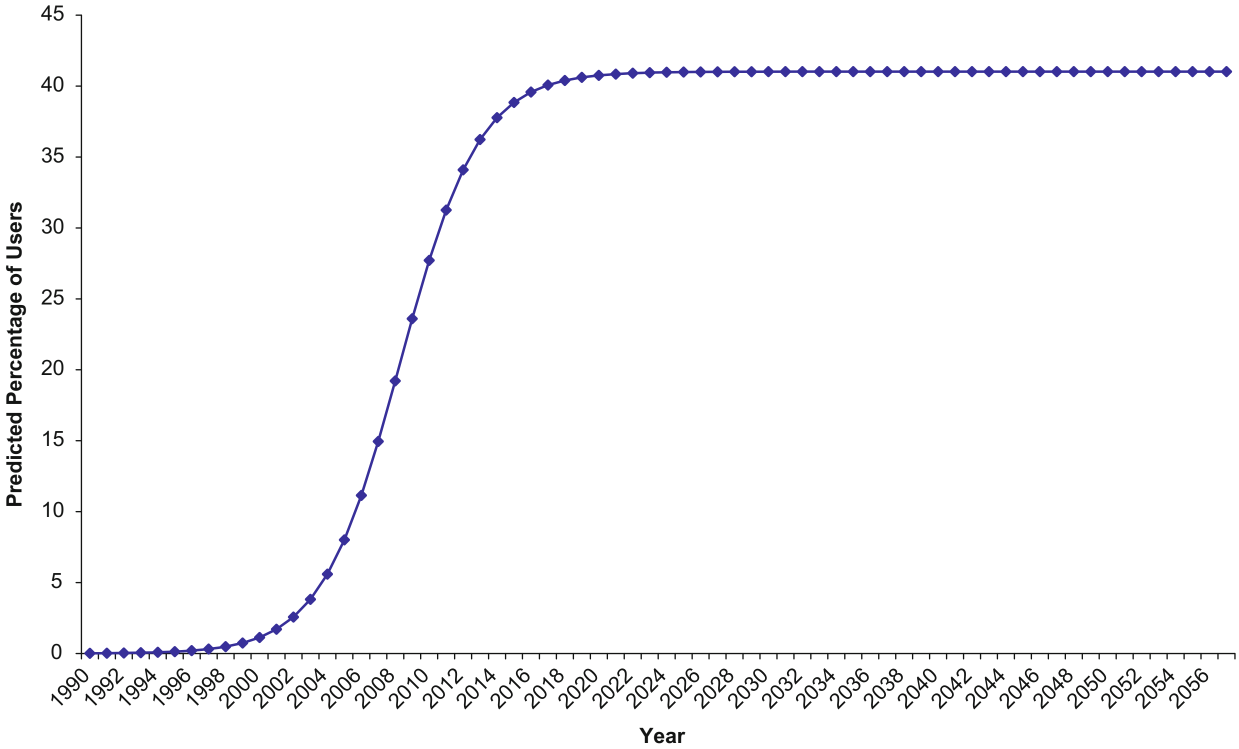

Fig. 6. Predicted catch-up in Internet adoption between low- and high-income countries.

2017) and 54 years (year 2057) to exactly converge to 41.03%, the long-term level of high-income countries. The conclusion from this simple exercise is that the implied rate of convergence is rather slow.

4.1. *Importance of including the first years of data*

Comín and Hobijn (2004) point out that the absence of the first years of data may have important consequences in the estimation of the diffusion process. The lack of public official statistics during the initial years in which a new technology is being used has been a problem in the vast majority of technologies that they study, as it is stated in their paper that "[…]*This selection effect therefore implies that data do not tend to cover the introductory phase*." The present study has the advantage of using data on the introductory phase for most countries.

In order to quantify the effect of including the initial years of data when estimating S-shapes, the methodology used in Comín, Hobijn, and Rovito (2008), henceforth CHR, is borrowed. In their paper they use three different calculations to argue that the logistic model fits the data much less so when they take into account the intensive margin of technological use. Their first strategy is to show that the computer routine to estimate the logistic curve does not converge in many cases once they control for this margin. Second, the estimate of the time parameter δ_2 is often negative, which is a direct violation of the logistic function.[16] Finally, they use the fact that the logistic curve predicts that diffusion of a given technology will reach 1% approximately at period $t=(-\ln(0.99)-\delta_1)/\delta_2$. They find that this date is systematically over or understated once the intensive margin is controlled for.

The strategy here is to show how the estimation changes once a given fraction of the initial years of data is omitted. In particular, the choice is made to eliminate the data below the 25th percentile of Internet users in every country.

It is found, as in CHR, that some countries lose so many observations that their "restricted" estimation takes longer to converge or does so very inaccurately.[17] However, unlike in the CHR case, this is not the norm. Most times the "unrestricted" estimation (the one that contains all years of available data) takes longer to converge. This seems reasonable since the computer routine has to work with a considerably larger amount of information when the sample is unrestricted. It is believed the usual failure to converge in CHR once one includes the intensive margin is due to the fact that the shape of the curve is fundamentally changed due to this inclusion. In the present case though, the shape of the curve is truncated,

[16] Logistic curves increase monotonically and hence the parameter δ_2 must be positive. Another consequence of this monotonicity is that the R^2 are artificially high and cannot be used as an informative measure of goodness- of- fit.

[17] In some cases the non-linear-least-squares estimator fails to produce standard errors for some or all of the parameters and the R^2's are missing too.

but not drastically altered. For the same reason no countries (or groups of countries) are found to have a negative estimate of δ_2.

However, the data show that the prediction of the period at which Internet diffusion reaches 1%, significantly changes when one omits the initial years of data—there is a very clear tendency to underestimate the number of periods necessary to reach this level. The intuition for this finding is clear. By losing the introductory phase of Internet diffusion, the estimated S-shape tends to display an artificially large slope, which evidently implies that the 1% level of adoption is reached much earlier than what the actual data show. Table A3 in Appendix A shows this in more detail. This table shows the estimates of the "1% date" for each country using the unrestricted and the restricted samples (columns 2 and 3, respectively), their difference (column 4), and the actual date at which the country has reached at least 1% of users (column 5).[18] The first thing to notice is that, perhaps not surprisingly, the difference between the two estimates is virtually always positive.[19] As discussed above, this indicates that, if one considers all the available data, the resulting S-shape has a lower slope and so the 1% level is predicted to be reached later in time. The bias of these estimates is then calculated by subtracting the estimated data from the actual.[20] In the unrestricted sample (column 6) there is a tendency to underestimate the 1% date, leading to "too pessimistic" predictions. The median bias is -2.84 years. The restricted sample (column 7) has a median bias of 2.51 years, leading to "too optimistic" predictions of when a country will reach the 1% level. While the two biases are similar in magnitude, these results show that including or excluding the initial years has important implications for the way one should interpret the estimates. In particular, the widespread omission of the initial years leads to predictions that are too generous. Figs. 7–9 in Appendix A illustrate this point for three developing countries. It is apparent that, by omitting the initial years of data, the slopes of the S-curves are much steeper in the "initial phase" and hence the Internet is predicted to spread much faster than it actually does.

5. The determinants of Internet adoption

To identify the main determinants of Internet adoption, this paper follows Estache et al. (2002) and Caselli and Coleman (2001) and estimates the following reduced form model:

$$\ln IU_{it} = \alpha + \beta_1 \ln Y_{it} + \beta_2 \ln P_{it} + \beta_3 \ln L_{it} + \beta_4 \ln C_{it} + \eta_i + \varepsilon_{it} \tag{2}$$

where IU_{it} represents the number of Internet users per capita in country i and period t, Y_{it} is the real GDP per capita, P_{it} represents the real cost of a local phone call, and L_{it} and C_{it} are the number of phone lines and computers per capita, respectively. The last two variables are intended to capture the level of telecommunication infrastructure and the availability of infrastructure facilities needed to access the Internet of a country at a given point in time, respectively. Finally, η_i is a country fixed effect and ε_{it} is a standard error term.

One would expect β_1 to be positive since a higher income level is naturally associated with better technological infrastructure and a higher purchasing power of goods and services associated with the Internet. The coefficient of the cost of a local phone call (β_2) is expected to be negative and its magnitude would depend on the price elasticity of the demand for Internet usage. Both the effects of the number of phone lines (β_3) and the number of computers (β_4) should be positive, since they are necessary inputs to use the Internet.[21] Moreover, one would expect a strong positive complementarity between computer and Internet use.

Some studies have added additional explanatory variables to Eq. (2), including a country's level of human capital (proxied by the number of years of education), its degree of trade openness, the percentage of urban population, and the extent of property rights protection.[22] These variables are not incorporated here since the data suggest that, in most cases, they display very little variation in the time interval covered in this paper. The inclusion of a country fixed effect in the estimation should be able to capture most of the cross-country differences explained by these variables.[23]

One variable that deserves special mention is the quality of institutions. One of the most established facts in the comparative telecommunication literature is that institutions are important determinants of the diffusion of telecommunication technologies.[24] In results not reported here it is demonstrated that the same is true in the current sample. When one estimates Eq. (2) in *growth rates*, the quality of institutions (measured by the lag of the *level of*

[18] In this exercise it is found that 62 countries never reach the 1% diffusion level and are therefore omitted from the calculations.

[19] Only in two out of the 143 countries is the difference negative.

[20] Similar results are obtained when countries are grouped in two different income groups or when a different percentile is used to truncate the data. These results are available from the authors upon request.

[21] A possible criticism to the specification of the model is the inclusion of the cost of local phone calls given the increase in alternative technologies to access the Internet (for instance broadband access). However, up to 2004 the participation of alternative technologies was very low, especially in low income countries.

[22] See Chinn and Fairlie (2007), Wallsten (2005), Kiiski and Pohjola (2002), and Chong and Micco (2003).

[23] Interestingly, the coefficients associated to these variables have often been found non-significant or controversial in Internet adoption models. This is the case of education in Kiiski and Pohjola (2002) and Chinn and Fairlie (2007), and openness and property rights protection in Caselli and Coleman (2001).

[24] Levy and Spiller (1996) and Henisz and Zelner (2001) provide theoretical reasons why this should be the case. Empirically, Andonova and Díaz-Serrano (2009), Andonova (2006), and Guillén and Suárez (2005) show a positive relationship between a country's institutional framework and its diffusion of different technologies, the Internet in particular.

Table 2
Benchmark model.

log real GDP per capita	2.15***
	(0.51)
log real cost	−0.2***
	(0.08)
log lines per capita	2.13***
	(0.27)
log computers per capita	2.32***
	(0.13)
Constant	−11.44***
	(4.7)
Method of estimation	OLS
Number of observations	949
R^2	0.91

The dependent variable is the log number of Internet users per capita. Robust standard errors in parentheses; *,**, and *** denote significance at the 10%, 5%, and 1% level, respectively.

constraints on executive discretion) has a significant positive effect on the growth rate of the number of per capita Internet users and hosts.[25] However, the effect of institutions becomes insignificant when one estimates the equation in *levels*. The interpretation of this result is that the level of Internet usage in a given country is better explained by country fixed effects or by its level of infrastructure (number of computers and telephone lines per capita), as the estimates below suggest.

The results of Eq. (2) using OLS are presented in Table 2.[26] All the coefficients are highly significant and have the expected signs. The levels of income and telecommunication infrastructure (lines and computers per capita) have significant positive effects on Internet adoption and are similar in magnitude. A 10% increase in per capita GDP is associated with a 21.5% increase in the number of Internet users per capita. Similarly, increases of 10% in the number of lines and computers per capita drive up the number of Internet users per capita by 21.3% and 23.2%, respectively. On the contrary, the higher the cost of a local call, the lower is the percentage of population that uses the Internet, although this coefficient is significantly smaller.

5.1. The diffusion model

The specification of Eq. (2) has often been criticized because it does not account for the process of diffusion in Internet adoption. Following Estache et al. (2002), the next regression includes the lag of the number of Internet users (in logs) as a right-hand-side variable:

$$\ln IU_{it} = \alpha_i + \beta_1 \ln Y_{it} + \beta_2 \ln P_{it} + \beta_3 \ln L_{it} + \beta_4 \ln C_{it} + \beta_5 \ln IU_{it-1} + \eta_i + \varepsilon_{it} \tag{3}$$

Eq. (3) is the reduced form of a Gompertz model of technology diffusion with a constant speed of adjustment. In such a model, the change in the number of users (from the current period to the next one) is expressed as a fraction (the speed of adjustment) of the gap between the number of users in equilibrium and the number of current users. Hence, the number of new users who adopt a certain good or service in a given period depends on both the number of existing and potential users, which is itself determined by demand-side variables (income, costs, etc.), and other factors affecting the demand or supply conditions or the technological infrastructure in each country *i* (see Estache et al., 2002; Kiiski & Pohjola, 2002; Stoneman, 1983 for more details).

The coefficient β_5 measures the importance of network externalities in the diffusion of the Internet. In the absence of diffusion, β_5 should not be significant. When β_5 is positive and smaller than 1, the diffusion model is accepted: the number of users in the current period helps explain the number of Internet users in the subsequent year.

As is well known, including the lagged dependent variable in the right hand side of Eq. (3) creates an endogeneity problem. By construction, the regressor $\ln IU_{it-1}$ is correlated with the error term ε_{is} for $s < t$, so the standard fixed effects estimation is not consistent (see Wooldridge, 2002). To correct this problem, use is made of the instrumental variables (IVs) procedure proposed by Arellano and Bond (1991), where the lagged values of the dependent variable are used as instruments. Table 3 presents the results of the OLS and IV estimations (specifications (1) and (2), respectively).

First of all, the diffusion coefficient (the lag of the dependent variable) is positive, smaller than one, and highly significant with a similar magnitude in both regressions, indicating that the diffusion model cannot be rejected. A 10% increase in the number of Internet users per capita in the current year leads to an increase of about 5–6.8% in the number of

[25] In the sample, institutions are a significant explanatory variable when one uses system GMM, but not when one uses standard GMM techniques. This is consistent with Andonova and Díaz-Serrano (2009), who claim that the former technique is more adequate in this framework.

[26] In all the OLS regressions that follow, robust standard errors are used to account for potential heteroskedasticity of the unbalanced panel. Also, year effects are added to control for time-varying macroeconomic shocks. The inclusion of these regressors do not change any result significantly, so their associated coefficients are not shown here in order to save space. The inclusion of continent effects (as in Estache et al., 2002) is also irrelevant for the findings.

Table 3
OLS and instrumental variable estimations of the diffusion model.

	[1]	[2]
log real GDP per capita	0.866***	2.03***
	(0.02)	(0.42)
log real cost	0.01	0.04
	(0.02)	(0.05)
log lines per capita	0.01	0.3*
	(0.14)	(0.16)
log computers per capita	0.52***	0.995***
	(0.08)	(0.1)
lag Internet users	0.676***	0.496***
	(0.02)	(0.02)
Constant	−6.69***	−15.33***
	(2.43)	(3.86)
Method of estimation	OLS	IV
Number of observations	881	759
R^2	0.97	–

The dependent variable is the log number of Internet users per capita. Robust standard errors in parentheses in specification [1] and standard errors in parenthesis in specification [2]; *,**, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Internet users the next year. In the OLS regression (column [1]), income and the number of computers per capita have a positive effect on diffusion. It is interesting to note that the size of these estimates becomes much larger once the endogeneity problems are taken into account and an instrumental variables procedure is used (column [2]). Another difference between the two specifications is that the number of telephone lines per capita is statistically significant and has the expected sign only when one uses instruments. Finally, it is worth mentioning that, if one includes a year effect to capture macroeconomic shocks, the coefficient on the real GDP per capita turns insignificant. Interestingly, this does not happen to the other variables that have clearly increased in the time period studied, namely the number of telephone lines and computers per capita. This suggests that the positive coefficient on income should be interpreted with caution, since it seems to be picking up (at least partly) the time trend.

The importance of the lagged dependent variable is in line with the results of several papers, including Goolsbee and Klenow (2002) and Kiiski and Pohjola (2002). However, it contradicts the results of Estache et al. (2002), where the diffusion hypothesis is rejected. There are several reasons why the present results differ from theirs. The first one is that the sample used here is considerably larger. In particular, there are 74 countries that are included in this sample but not in theirs. Moreover, for many countries they do not have access to data for the initial years. Additionally, the time span here is longer (it includes the 2000–2003 period), whereas their sample ends in 1999. Finally, from an econometric point of view, the Arellano–Bond GMM estimator is used, which is known to be more efficient than the Anderson–Hsiao IV estimator that they use.

The main new result of this section is that network externalities drive Internet diffusion and are indeed one of its most important determinants. The fact that in both the OLS and the IV specifications the lagged dependent variable is one of the significant explanatory variables gives strong support to this hypothesis.

Tables 2 and 3 provide results on the determinants of Internet diffusion at the world level. However, Section 4 presents conclusive evidence that the process of Internet diffusion is far from being uniform across countries. Thus, the question that needs to be answered next is whether the variables that explain this process differ between low- and high-income countries. Only by identifying differences in the explanatory power of factors that influence the diffusion process in the two groups will it be possible to adopt policies aimed at reducing the digital divide.

5.2. Does the magnitude of Internet diffusion explanatory variables vary with the level of income?

The benchmark model showed that the level of income is positively and highly correlated with Internet adoption. However, this result does not provide information about the existent varying processes of Internet adoption across countries with different levels of income. To assess whether there are significant differences in the explanatory power of the variables that are more likely to account for the Internet diffusion process, Eq. (3) is estimated, dividing the sample into two groups: low- and high-income countries.

Table 4 displays the estimation results for the two different groups of countries. The table shows that the number of users in the previous period is significant for both groups of countries.[27] This result confirms that network effects are one of the main drivers of Internet diffusion.

The estimates indicate that network effects are larger in high-income countries. A 10% increase in the number of Internet users in high-income countries in 1 year leads to an increase of almost 6% in the number of users the following

[27] The rest of the paper relies on the IV estimation only.

Table 4
Impact of income categories on the diffusion process.

	Low income [1]	High income [2]
log real GDP per capita	2.69***	0.6
	(0.88)	(0.42)
log real cost	0.13*	−0.14**
	(0.07)	(0.06)
log lines per capita	0.82***	−0.04
	(0.29)	(0.21)
log computers per capita	0.89***	0.998***
	(0.14)	(0.13)
lag Internet users	0.44***	0.59***
	(0.03)	(0.03)
Constant	−16.17**	−5.44
	(7.3)	(4.26)
Method of estimation	IV	IV
Number of observations	356	399

The dependent variable is the log number of Internet users per capita. Standard errors in parenthesis; *,**, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table 5
World diffusion and diffusion by income category: 1985–1998 and 1999–2004.

	Low income		High income		World	
	1985–1998 [1]	1999–2004 [2]	1985–1998 [3]	1999–2004 [4]	1985–1998 [5]	1999–2004 [6]
log real GDP per capita	2.62	2.81***	2.84***	0.43	3.43***	1.21***
	(2.15)	(0.997)	(0.81)	(0.49)	(0.81)	(0.55)
log real cost	0.11	0.13*	−0.03	−0.05	0.05	0.08
	(0.19)	(0.07)	(0.11)	(0.08)	(0.1)	(0.05)
log lines per capita	1.36*	0.79**	−1.16***	0.7**	−0.16	1.07***
	(0.74)	(0.33)	(0.36)	(0.34)	(0.33)	(0.23)
log computers per capita	1.16***	0.69***	1.33***	0.57***	1.35***	0.68***
	(0.28)	(0.17)	(0.19)	(0.17)	(0.16)	(0.13)
lag Internet users	0.32***	0.48***	0.51***	0.56***	0.42***	0.48***
	(0.07)	(0.04)	(0.04)	(0.05)	(0.04)	(0.03)
Constant	−14.04	−17.48**	−27.3***	−3.27	−28.87***	−6.69
	(17.95)	(8.28)	(8.09)	(4.85)	(7.62)	(4.89)
Method of estimation	IV	IV	IV	IV	IV	IV
Number of observations	101	255	209	190	310	449

The dependent variable is the log number of Internet users per capita. Standard errors in parenthesis; *,**, and *** denote significance at the 10%, 5%, and 1% level, respectively

year, which is 1.5% more than in low-income countries. One possible explanation for this finding may be related to the way in which developed economies are structured. The relative importance of services (usually highly intensive in Internet usage) in these economies is higher than in less developed ones. Accordingly, high-income countries may have more Internet-demanding and network-demanding jobs, hence enhancing the importance of network effects.

It is also interesting to note that, while income level (measured by GDP per capita) is a very important determinant of Internet adoption for low-income countries, it is not significant for high-income countries. In other words, when countries that already have a high-income level are considered, changes in GDP per capita do not have a significant impact on the level of Internet adoption. This result is similar to the one in Beilock and Dimitrova (2003), who show that income differences have a larger effect in the use of the Internet at lower income levels. Finally, somewhat surprisingly, the coefficient associated to the real cost has a positive sign for low-income countries, while the one corresponding to the number of lines per capita is negative –although not significant- for high-income countries.

In addition to studying the determinants of Internet adoption dividing countries by income level, it is important to understand whether the differential effect at different levels of income is constant through time. In order to do so, the sample is divided into two sub-periods: 1985–1998 and 1999–2004. The results are presented in Table 5.

First, the model of diffusion is accepted in both sub-periods and for both income categories. Moreover, the table also shows that the importance of network effects has increased over time for the two groups. Between the years 1985 and 1998, an increase of 10% in the number of Internet users per capita in low-income countries in 1 year produced a 3.2% increase in the number of users the next year. During the 1999–2004 period the boost was 4.8%. A similar result holds for high-income countries—the diffusion coefficient increases from 0.51 for the period 1985–1998 to 0.56 for the period

Table 6
Impact of the number of internet service providers on the internet diffusion process.

	Low income			High income		
	$1 \leq ISP \leq 4$ [1]	$ISP \geq 5$ [2]	All [3]	$1 \leq ISP \leq 4$ [4]	$ISP \geq 5$ [5]	All [6]
log real GDP per capita	3.07***	1.36	2.66***	1.76**	0.24	0.86**
	(1.1)	(1.42)	(0.9)	(0.69)	(0.49)	(0.42)
log real cost	0.15	0.05	0.13*	−0.07	−0.12*	−0.12*
	(0.11)	(0.08)	(0.07)	(0.14)	(0.07)	(0.06)
log lines per capita	1.01***	0.59	0.81***	0.98**	−0.03	0.16
	(0.34)	(0.5)	(0.29)	(0.41)	(0.22)	(0.21)
log computers per capita	0.96***	0.55***	0.89***	0.97***	0.62***	0.94***
	(0.17)	(0.2)	(0.14)	(0.2)	(0.16)	(0.13)
lag Internet users	0.41***	0.55***	0.44***	0.38***	0.72***	0.46***
	(0.04)	(0.05)	(0.03)	(0.06)	(0.04)	(0.04)
lag Internet users × ISP_5			0.006			0.15***
			(0.03)			(0.02)
Constant	−17.02*	−9.23	−15.96**	−14.96**	−2.27	−7.78*
	(8.89)	(12.29)	(7.4)	(6.71)	(5.02)	(4.17)
Method of estimation	IV	IV	IV	IV	IV	IV
Number of observations	246	108	356	113	286	399

The dependent variable is the log number of Internet users per capita. Standard errors in parenthesis; *,**, and *** denote significance at the 10%, 5%, and 1% level, respectively.

1999–2004. Worldwide the increase is from 0.42 to 0.48. Interestingly, these estimates are consistent with the S-shape curves estimated for each income category in Section 4. The value of the lagged number of Internet users captures the average contribution of network effects to the speed of adoption and thus shows that the speed of diffusion increases between the two periods considered in this exercise. This indicates that one is identifying the first phase of the Internet adoption process. These results also show how low-income countries are following a similar adoption path to the one observed for high-income countries; the diffusion coefficient for the 1999–2004 period for low-income countries is very close in magnitude to the one obtained for the period 1985–1998 for the group of developed countries (0.48 vs. 0.51).

The cutoff dates used in Table 5 to divide periods are clearly arbitrary. Indeed, one could easily argue that they should differ between the two groups of countries, reflecting the fact that they are at different stages of the diffusion process. Results not reported here show that the same qualitative results hold if different splitting years (1995, 2000) for low- and high-income countries are used. In the two groups, income per capita is insignificant at high levels of competition (specifications [2] and [5]). The real cost has the right sign and is significant only in specifications [5] and [6]. Finally, lines per capita matter more for low-income countries.

The conclusion from this section is that the diffusion model is accepted in virtually all cases, regardless of the cutoff used or the income group chosen.[28] When one chooses the cutoff of 1995 it is still the case that the importance of network effects increases over time. However, this is not the case when the dividing year is set to be the year 2000. One interpretation of this result is that these effects have tended to vanish by the end of the studied period, perhaps because of the fading impact of the IT revolution in the 1990s and the economic crisis after the burst of the dot-com bubble.

5.3. Impact of the level of competition on Internet diffusion

As mentioned in the introduction, there is plenty of evidence that the adoptions of information and communication technologies in general and the Internet in particular significantly contribute to economic growth and development (for a summary of this literature see Grace, Kenny, & Zhen-Wei Qiang, 2004; Zhen-Wei Qiang & Pitt, 2003). Thus, a key policy question centers on what low-income countries can do to accelerate Internet diffusion. One potentially positive policy is to liberalize telecommunication markets, with the hope that more competition drives prices down and facilitates diffusion of the Internet. To assess the validity of this argument, the impact of the number of Internet Service Providers (ISPs) operating in a country on the speed of diffusion is analyzed. The sample is decomposed into two groups: countries with a low level of competition—with a number of ISPs less than or equal to 4, and countries with a high level of competition—with a number of ISPs greater than 4.[29] Then, Eqs. (2) and (3) are estimated for each group, also distinguishing between low- and high-income countries. Provided the lag variable of Internet users is, *ceteris paribus*, a proxy for the average speed of diffusion,

[28] The coefficient on the lag is insignificant when one chooses the cut-off 1995 for low-income countries. The most likely reason is that the number of observations drops drastically to 13.

[29] The median of the number of ISPs for the world is 5. This threshold is adopted to define countries with low and high competition. In unreported results, whether changing the definition of this cutoff value has any effect on the results is tested. Changing the threshold to 4 (the median number of ISPs for low income countries) or to 17 (the median number of ISPs for high income countries) does not have a significant qualitative impact on the estimates.

the interest is in determining if a more competitive ISP market structure leads to a higher estimate of the lagged Internet users variable.

The results are displayed in Table 6. First, once again, the model of diffusion cannot be rejected. Network effects are a significant determinant of Internet adoption for all income categories and degrees of competition. Second, competition has a larger impact on diffusion in high-income countries. In low-income countries increasing the number of ISPs from 4 or less to 5 or more increases the diffusion coefficient from 0.41 to 0.55, while for high-income countries the jump is from 0.38 to 0.72. Supporting this finding, specifications [3] and [6] show that, when one uses the interaction between high competition (proxied by the dummy variable ISP_5, which takes a value of 1 if there are 5 or more ISP providers) and lagged Internet users, a high degree of competition significantly increases the average speed of diffusion in high-income countries while the effect is insignificant in low-income countries. This approach seems to be more informative than the one used in Estache et al. (2002) and Wallsten (2005), who simply added a dummy variable on the right hand side of their regression to account for the existence of competition and/or regulation. In fact, this latter work only allows the intercept to adjust for the conditions on the telecommunication market while the approach here allows all coefficients to adjust for the degree of competition.

6. Conclusions

This paper provides a detailed empirical study of the process of adoption and diffusion of the Internet in a large sample of countries for the period 1990–2004. In the first part of the paper it is shown that Internet adoption follows an S-shape pattern, but that this pattern is different for low- and high-income countries. Internet diffusion in low-income countries started with a lag but is now enjoying a faster adoption speed. However, the estimates suggest that the digital divide, in absolute terms, is still impressive and it might take low-income countries several decades to eliminate it.

A major feature that distinguishes this work from previous papers in the literature on diffusion of new technologies is that the data set covers the first years in which the innovation (i.e. Internet) was adopted. This allows the provision of more realistic estimations on the actual diffusion process.

The second part of the paper explores the main determinants of Internet diffusion and finds that national network effects—measured as the lag of the number of users per capita in a given country—are a crucial determinant of Internet adoption. The results show that this network effect is very robust and stronger in high-income countries, implying that low- and high-income countries clearly in different phases of the process of Internet adoption during the period 1990–2004. The paper also explores potential differences in this process across time and finds that low-income countries are following the path of high-income countries. A positive reading of these results is that low-income countries are, albeit at a very slow pace, converging to the levels of Internet usage present in high-income countries. Finally, the results show that increasing the number of Internet providers has a positive effect on the spread of the Internet. An important policy implication of these findings is that, in order to help close the digital divide, policymakers may want to implement policies to liberalize the telecommunication markets.[30] However, further analysis is needed to design a proper strategy to do so.

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Appendix A

See Tables A1, A2 and A3.

A.1. World Bank income classification[31]

Low-income countries: Afghanistan, Bangladesh, Benin, Bhutan, Burkina Faso, Burundi, Cambodia, Central African Republic, Chad, Comoros, Congo (Dem. Rep.), Cote d'Ivoire, Eritrea, Ethiopia, Gambia, Ghana, Guinea, Guinea-Bissau, Haiti, India, Kenya, Korea (Dem Rep.), Kyrgyz Republic, Lao PDR, Liberia, Madagascar, Malawi, Mali, Mauritania, Mongolia, Mozambique,

[30] As argued in Estache et al. (2002), such policies have been recently implemented in several Latin American countries, like Chile, Argentina, and Mexico.

[31] *Source*: The World Bank website as of April 2007. Link: http://web.worldbank.org/WBSITE/EXTERNAL/DATASTATISTICS/0,,contentMDK:20420458~menuPK:64133156~pagePK:64133150~piPK:64133175~theSitePK:239419,00.html

Table A1
Descriptive statistics for number of Internet users.

Year	Observations	Mean	Standard dev.	Min	Max
1990	214	12.34	137.2	0	2000
1991	214	108	472	0	3000
1992	214	136.3	628.6	0	4500
1993	214	152.5	739.3	0	6000
1994	214	223.8	1358.4	0	13000
1995	214	284.7	2130.7	0	25000
1996	214	415.2	3404.5	0	45000
1997	214	623	4487.6	0	60000
1998	214	941.5	6263.7	100	84600
1999	214	1364	7665.9	300	102000
2000	213	1903.6	9551.9	500	124000
2001	213	2405.3	11300	0	143000
2002	214	3082.3	13200	1000	159000
2003	213	3602.3	14100	1400	162000
2004	213	4249.5	16200	1600	185000

The mean, minimum, and maximum figures are in thousands.

Table A2
Descriptive statistics for Internet users per capita.

Year	Observations	Mean	Standard dev.	Min.	Max.
1990	214	0.024	0.11	0	0.8
1991	214	0.05	0.21	0	1.4
1992	214	0.09	0.34	0	2.21
1993	214	0.14	0.46	0	2.77
1994	214	0.29	0.89	0	6.75
1995	214	0.62	1.75	0	13.71
1996	214	1.2	2.92	0	18.2
1997	214	2.11	4.54	0	27.49
1998	214	3.43	6.59	0	36.33
1999	214	5.43	9.57	0	53.82
2000	213	8.08	12.16	0	59.79
2001	213	10.1	14.27	0	59.93
2002	214	12.25	16.14	0	64.79
2003	213	14.34	17.45	0	67.47
2004	213	16.59	19.45	0	77

The mean, minimum and maximum figures are in percentages.

Myanmar, Nepal, Niger, Nigeria, Pakistan, Papua New Guinea, Rwanda, Sao Tome and Principe, Senegal, Sierra Leone, Solomon Islands, Somalia, Sudan, Tajikistan, Tanzania, Togo, Uganda, Uzbekistan, Vietnam, Yemen, Zambia, Zimbabwe.

Lower-middle-income countries: Albania, Algeria, Angola, Armenia, Azerbaijan, Belarus, Bolivia, Bosnia and Herzegovina, Brazil, Bulgaria, Cameroon, Cape Verde, China, Colombia, Congo (Rep), Cuba, Djibouti, Dominican Republic, Ecuador, Egypt, El Salvador, Fiji, Georgia, Guatemala, Guyana, Honduras, Indonesia, Iran, Iraq, Jamaica, Jordan, Kazakhstan, Kiribati, Lesotho, Macedonia, Maldives, Marshall Islands, Micronesia, Moldova, Morocco, Namibia, Nicaragua, Paraguay, Peru, Philippines, Sri Lanka, Suriname, Swaziland, Syrian Arab Republic, Thailand, Tonga, Tunisia, Turkmenistan, Ukraine, Vanuatu, West Bank and Gaza.

Upper-middle-income countries: American Samoa, Argentina, Barbados, Belize, Botswana, Chile, Costa Rica, Croatia, Czech Republic, Dominica, Equatorial Guinea, Estonia, Gabon, Grenada, Hungary, Latvia, Lebanon, Libya, Lithuania, Malaysia, Mauritius, Mayotte, Mexico, Northern Mariana Islands, Oman, Palau, Panama, Poland, Romania, Russian Federation, Seychelles, Slovak Republic, South Africa, St. Vincent and the Grenadines, Trinidad and Tobago, Turkey, Uruguay, Venezuela.

High-income countries: Andorra, Antigua and Barbuda, Aruba, Australia, Austria, Bahamas, Bahrain, Belgium, Bermuda, Brunei Darussalam, Canada, Cayman Islands, Cyprus, Denmark, Finland, France, French Polynesia, Germany, Greece, Greenland, Guam, Hong Kong (China), Iceland, Ireland, Israel, Italy, Japan, Korea (Rep), Kuwait, Liechtenstein, Luxembourg, Macao (China), Malta, Monaco, Netherlands, Netherlands Antilles, New Caledonia, New Zealand, Norway, Portugal, Puerto Rico, Qatar, San Marino, Saudi Arabia, Singapore, Slovenia, Spain, Sweden, Switzerland, United Arab Emirates, United Kingdom, United States, Virgin Islands (US).

Table A3
Calculation of the bias in the date at which 1% of the population uses Internet using unrestricted and restricted samples.

Country	*t* unrestricted	*t* restricted	Difference	Actual *t*	Bias unrestricted	Bias restricted
Albania	24.59	17.50	7.09	15	−9.59	−2.50
Algeria	27.66	21.60	6.06	7	−20.66	−14.60
Andorra	10.45	6.73	3.72	7	−3.45	0.27
Angola	26.35	18.26	8.09	15	−11.35	−3.26
Antigua and Barbuda	39.53	31.84	7.69	6	−33.53	−25.84
Argentina	11.58	6.56	5.02	10	−1.58	3.44
Armenia	14.35	8.33	6.02	11	−3.35	2.67
Aruba	10.96	1.98	8.98	17	6.04	15.02
Australia	11.08	8.13	2.95	2	−9.08	−6.13
Austria	10.03	7.04	2.99	5	−5.03	−2.04
Bahamas	12.77	5.75	7.02	7	−5.77	1.25
Bahrain	11.66	4.73	6.93	8	−3.66	3.27
Barbados	13.89	6.88	7.01	9	−4.89	2.12
Belarus	14.45	8.43	6.02	11	−3.45	2.57
Belgium	10.40	7.40	3.00	7	−3.40	−0.40
Belize	12.20	5.44	6.76	8	−4.20	2.56
Bermuda	8.87	2.56	6.31	6	−2.87	3.44
Bolivia	13.06	6.13	6.93	11	−2.06	4.87
Bosnia and Herzegovina	14.73	6.75	7.98	11	−3.73	4.25
Botswana	10.91	3.87	7.04	10	−0.91	6.13
Brazil	13.24	9.21	4.03	9	−4.24	−0.21
Brunei Darussalam	42.45	34.89	7.56	6	−36.45	−28.89
Bulgaria	15.30	10.54	4.76	8	−7.30	−2.54
Canada	9.76	6.76	3.00	4	−5.76	−2.76
Cape Verde	12.53	4.18	8.35	10	−2.53	5.82
Chile	10.95	5.93	5.02	8	−2.95	2.07
China	12.93	6.79	6.14	11	−1.93	4.21
Colombia	15.02	8.98	6.04	9	−6.02	0.02
Costa Rica	12.25	7.25	5.00	8	−4.25	0.75
Croatia	13.81	7.98	5.83	8	−5.81	0.02
Cuba	10.92	3.90	7.02	12	1.08	8.10
Cyprus	11.68	6.67	5.01	8	−3.68	1.33
Czech Republic	10.94	5.49	5.45	5	−5.94	−0.49
Denmark	9.35	6.33	3.02	5	−4.35	−1.33
Dominica	13.26	6.31	6.95	7	−6.26	0.69
Dominican Rep.	12.07	5.07	7.00	10	−2.07	4.93
Ecuador	11.76	10.80	0.96	11	−0.76	0.20
El Salvador	12.98	5.00	7.98	11	−1.98	6.00
Estonia	11.98	7.06	4.92	5	−6.98	−2.06
Faroe Islands	11.14	3.22	7.92	7	−4.14	3.78
Fiji	12.34	6.35	5.99	11	−1.34	4.65
Finland	9.24	6.24	3.00	2	−7.24	−4.24
France	11.74	8.75	2.99	6	−5.74	−2.75
French Guyana	11.70	3.70	8.00	10	−1.70	6.30
French Polynesia	9.86	2.87	6.99	9	−0.86	6.13
Gabon	10.40	2.41	7.99	11	0.60	8.59
Gambia	10.41	4.38	6.03	12	1.59	7.62
Germany	9.67	6.69	2.98	6	−3.67	−0.69
Gibraltar	10.37	2.35	8.01	8	−2.37	5.65
Greece	9.23	6.28	2.95	7	−2.23	0.72
Greenland	9.68	3.73	5.96	7	−2.68	3.27
Grenada	10.59	3.96	6.63	9	−1.59	5.04
Guadeloupe	10.88	3.89	6.99	10	−0.88	6.11
Guam	12.34	6.23	6.11	7	−5.34	0.77
Guatemala	24.75	18.87	5.89	12	−12.75	−6.87
Guernsey	10.92	3.87	7.05	7	−3.92	3.13
Guyana	11.91	4.86	7.05	10	−1.91	5.14
Honduras	10.35	4.34	6.01	11	0.65	6.66
Hongkong	12.14	9.10	3.04	4	−8.14	−5.10
Hungary	28.31	25.08	3.22	8	−20.31	−17.08
Iceland	8.52	1.42	7.10	3	−5.52	1.58
Indonesia	22.79	16.59	6.21	12	−10.79	−4.59
Iran	10.95	4.97	5.98	12	1.05	7.03
Ireland	8.52	5.53	2.99	6	−2.52	0.47
Israel	11.10	8.12	2.99	7	−4.10	−1.12
Italy	10.03	7.03	3.01	7	−3.03	−0.03
Jamaica	9.68	3.91	5.76	9	−0.68	5.09
Japan	10.71	7.67	3.05	6	−4.71	−1.67
Jersey	9.28	4.65	4.64	7	−2.28	2.35
Jordan	11.73	6.30	5.43	9	−2.73	2.70

Table A3 (*continued*)

Country	t unrestricted	t restricted	Difference	Actual t	Bias unrestricted	Bias restricted
Kazakhstan	10.86	4.83	6.03	12	1.14	7.17
Kiribati	10.16	1.87	8.29	10	−0.16	8.13
Korea (Rep. of)	10.22	7.23	2.99	7	−3.22	−0.23
Kuwait	10.51	5.57	4.94	8	−2.51	2.43
Kyrgyzstan	18.70	2.68	16.02	11	−7.70	8.32
Latvia	9.77	3.34	6.43	8	−1.77	4.66
Lebanon	9.29	3.31	5.99	8	−1.29	4.69
Lithuania	10.54	3.52	7.01	9	−1.54	5.48
Luxembourg	14.38	11.75	2.63	6	−8.38	−5.75
Macau	12.98	7.93	5.06	8	−4.98	0.07
Malaysia	10.30	6.29	4.01	8	−2.30	1.71
Maldives	12.50	5.24	7.26	10	−2.50	4.76
Malta	11.44	6.33	5.11	7	−4.44	0.67
Marshall Islands	9.91	0.87	9.04	11	1.09	10.13
Martinique	10.64	1.65	8.99	10	−0.64	8.35
Mauritius	10.02	3.03	6.99	9	−1.02	5.97
Mexico	11.27	8.27	3.00	9	−2.27	0.73
Micronesia	9.75	2.83	6.92	9	−0.75	6.17
Moldova	10.23	4.21	6.02	11	0.77	6.79
Mongolia	10.53	4.54	5.99	11	0.47	6.46
Morocco	11.58	5.59	5.99	12	0.42	6.41
Namibia	10.77	4.77	6.00	11	0.23	6.23
Netherlands	9.39	6.34	3.05	3	−6.39	−3.34
New Caledonia	10.57	4.55	6.02	9	−1.57	4.45
New Zealand	10.02	6.14	3.88	5	−5.02	−1.14
Nicaragua	12.59	6.78	5.81	12	−0.59	5.22
Norway	6.88	3.81	3.07	2	−4.88	−1.81
Oman	10.52	2.43	8.09	10	−0.52	7.57
Panama	9.92	3.95	5.97	9	−0.92	5.05
Paraguay	11.26	4.30	6.96	12	0.74	7.70
Peru	22.69	16.55	6.14	9	−13.69	−7.55
Philippines	9.78	3.77	6.01	9	−0.78	5.23
Poland	10.97	7.92	3.05	7	−3.97	−0.92
Portugal	8.86	5.87	2.99	6	−2.86	0.13
Puerto Rico	11.26	5.32	5.94	8	−3.26	2.68
Qatar	8.44	3.18	5.25	8	−0.44	4.82
Reunion	10.56	1.56	9.00	9	−1.56	7.44
Romania	9.53	4.57	4.96	9	−0.53	4.43
Russia	14.57	11.04	3.53	10	−4.57	−1.04
Saint Lucia	13.91	7.88	6.03	9	−4.91	1.12
San Marino	9.65	3.65	6.00	6	−3.65	2.35
Sao Tome and Principe	10.75	1.74	9.01	11	0.25	9.26
Saudi Arabia	11.32	5.31	6.01	11	−0.32	5.69
Senegal	22.55	16.43	6.12	12	−10.55	−4.43
Seychelles	10.63	3.71	6.92	8	−2.63	4.29
Singapore	10.35	7.43	2.92	5	−5.35	−2.43
Slovak Republic	10.82	5.79	5.03	8	−2.82	2.21
Slovenia	31.65	27.29	4.36	5	−26.65	−22.29
South Africa	9.79	6.79	3.00	8	−1.79	1.21
Spain	11.38	14.42	−3.04	7	−4.38	−7.42
Suriname	9.37	3.54	5.83	8	−1.37	4.46
Swaziland	10.56	4.58	5.99	12	1.44	7.42
Sweden	8.43	5.41	3.02	2	−6.43	−3.41
Switzerland	12.22	8.94	3.27	2	−10.22	−6.94
Macedonia	11.16	5.27	5.88	9	−2.16	3.73
Taiwan	9.84	6.85	2.99	6	−3.84	−0.85
Thailand	11.57	7.55	4.02	10	−1.57	2.45
Togo	10.86	3.84	7.01	11	0.14	7.16
Tonga	10.83	4.82	6.01	10	−0.83	5.18
Trinidad and Tobago	9.74	3.77	5.97	8	−1.74	4.23
Tunisia	10.75	4.76	5.99	10	−0.75	5.24
Turkey	10.64	5.63	5.01	10	−0.64	4.37
Ukraine	27.51	22.47	5.04	12	−15.51	−10.47
United Arab Emirates	10.08	4.03	6.04	8	−2.08	3.97
United Kingdom	9.99	6.88	3.11	5	−4.99	−1.88
United States	8.95	5.91	3.04	2	−6.95	−3.91
Uruguay	8.63	2.61	6.02	7	−1.63	4.39
Vanuatu	10.65	3.62	7.03	11	0.35	7.38
Venezuela	9.19	6.01	3.18	9	−0.19	2.99
Vietnam	17.19	10.03	7.17	12	−5.19	1.97
Virgin Islands	10.14	12.41	−2.27	6	−4.14	−6.41

Table A3 (*continued*)

Country	t unrestricted	t restricted	Difference	Actual t	Bias unrestricted	Bias restricted
Western Samoa	20.62	11.94	8.69	12	−8.62	0.06
Yugoslavia	10.79	3.81	6.99	11	0.21	7.19

The difference is calculated by subtracting restricted estimated date from the unrestricted one. The bias is defined as the difference between the actual date and the predicted one.

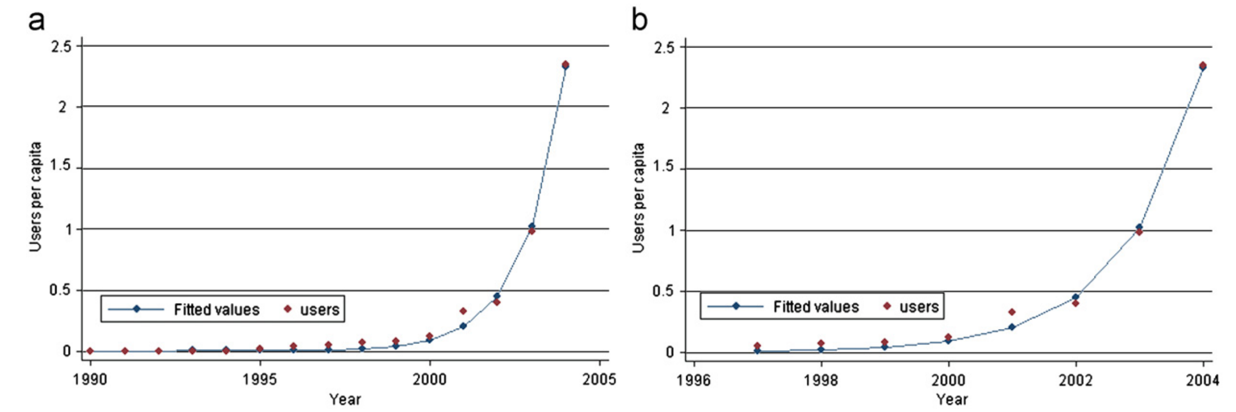

Fig. 7. (a) Predicted S-shape in Albania. (b) Predicted S-shape in Albania without initial years.

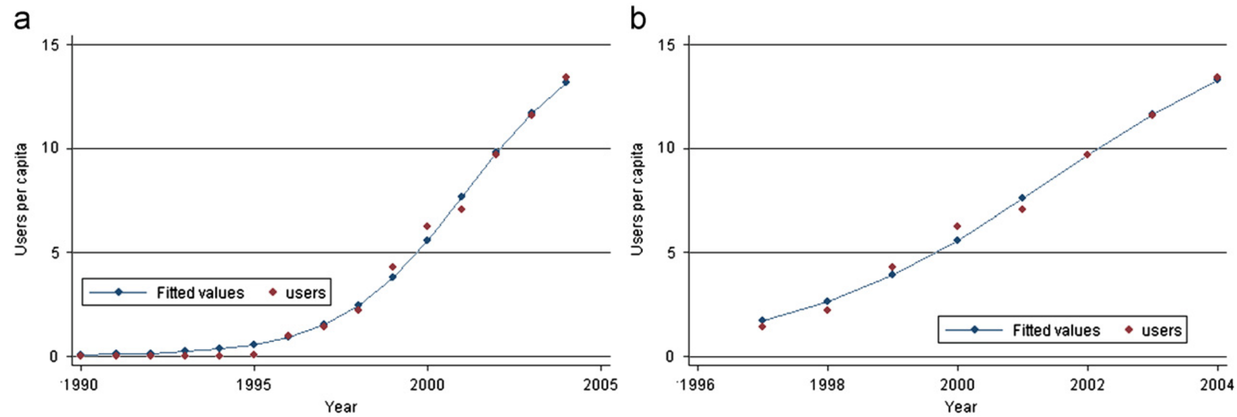

Fig. 8. (a) Predicted S-shape in Belize. (b) Predicted S-shape in Belize without initial years.

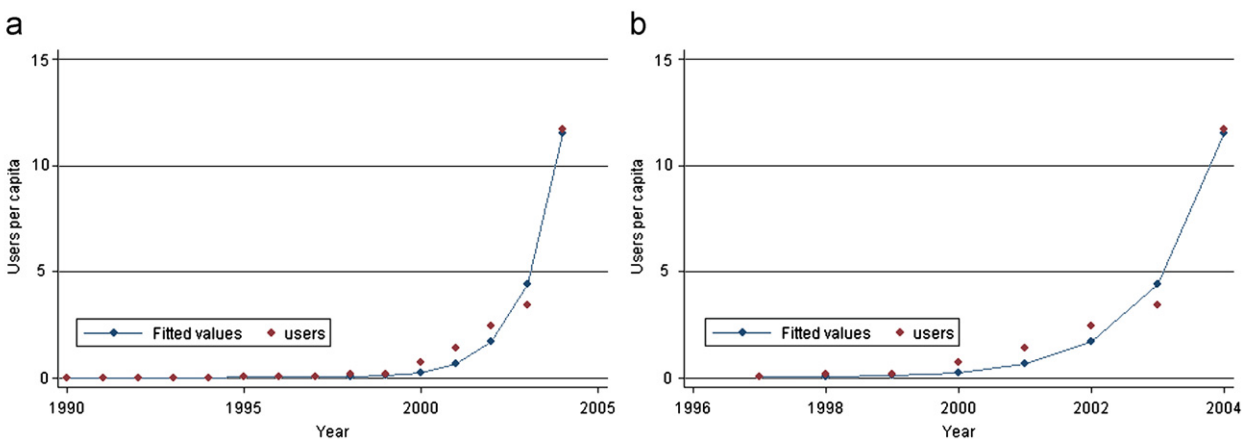

Fig. 9. (a) Predicted S-shape in Morocco. (b) Predicted S-shape in Morocco without initial years.

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