Working Paper, Nº 15/29
Madrid, November 2015

Heterogeneity and diffusion in the digital economy: Spain's case

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Abstract

The traditional Bass model (Bass, 1969) for the adoption and diffusion of new products has customarily been used to gauge the speed at which new products were adopted in a market by estimating innovation (p) and imitation (q) parameters. Rogers (2003) proposed that certain factors influence the diffusion of such products, including the educational level and age of consumers. In this article we estimate the coefficients of innovation and imitation for adopting internet, e-commerce and online banking in Spain's case, while controlling for heterogeneity of individuals according to educational level and age. We thus find that individuals with very different p and q coefficients can coexist in one market. We then verify that the processes of an ageing population and educational improvement in Spain could give rise to long term effects on Spain's overall innovative and imitative capacity as a result of its socio-demographic mix.

Key words: Digital economy, adoption, diffusion, consumers, Spain.

JEL: O30, L81, L86.

*: The authors would like to thank assistants to the Conference on Digital Experimentation CODE MIT (October 16th-17th, 2015) for their constructive and useful comments.

1 Introduction

The innovations that have been brought in over the last few decades within the ambit of digital media have entailed the most spectacular of changes as regards both the economy and social relations. The speed of this process and its reach to all corners of the world have transformed the various digital channels into a key factor in the competitiveness of businesses and the growth of the world economy. Traditionally, the dynamics whereby a product is adopted or acquired by a market have been approached using so-called *diffusion models*. This kind of model looks at the sales growth of an innovation and the factors determining the decision to acquire it by the adopters.

The pioneering papers (Rogers, 1962; Fourt & Woodlock, 1960; Mansfield, 1961; Bass, 1969) were oriented towards areas of marketing and were aimed at modelling diffusion for ends that were descriptive and that predicted expected sales for a new product by using a purely deterministic approach. Their mathematical formulation is based on epidemic propagation models (Bailey, 1957) which describe both how and how fast a viral disease can spread among a population potentially susceptible to infection.

The Bass model (1969) seeks to quantify the number of consumers who are going to acquire or use a new product or technology at a moment in time, principally by estimating an initial parameter (p), also known as the coefficient of innovation, which is the probability of an innovator adopting the product in time (t). The other parameter (q), the coefficient of imitation, is the probability of an individual classified as an imitator adopting a new product in the same time (t). This last parameter describes a type of diffusion via word-of-mouth, the mass media and the inter-relationship that exists between innovators and imitators. Estimation of this model in numerous works gave rise to a pattern in the cumulative adoption of an innovation that followed a typical S-curve. There are innumerable studies which have been made since then and which estimate the p and q values for highly diverse products.

The explanatory factors that were behind these deterministic trends were developed by Rogers (1962, 1983, 1995, 2003). According to Rogers (2003), diffusion is the process whereby an innovation is transmitted over time among the members of a market through certain channels. This line of work was more oriented toward the realm of consumer behaviour, where positive analyses were conducted with respect to variables that affect the probability of adopting an innovation and the time horizon in which this occurred. The adoption of an innovation depends on several factors, such as the relative advantage of an innovation compared to pre-existing products, its compatibility with the life-style habits of the potential adopter, complexity of use, or the chances of using it before acquiring it.

The issue we raise in this paper is whether all these factors conditioning the adoption of an innovation can affect the innovative or imitative behaviour of consumers in very different ways depending on their socio-economic attributes. For example, the perception of the difficulty involved in using the internet may be very different for a young university student compared to an 80-year-old pensioner only educated to primary level. It might also be the case that the benefits of using online banking services for a person who is working with a computer are very distinct from those apparent to a pensioner who has more time to visit a bank branch. All such circumstances might mean that in any single market there are consumers who have very different p and q values from each other.

In this paper, we will estimate the coefficients of innovation and imitation for heterogeneous representative individuals according to their educational level (primary, secondary or tertiary) and who are at any of three phases of their life cycle in age terms (study phase, work phase, retirement phase).

Trends in the socio-demographic composition of such a population might give rise to changes in a country's overall innovative and imitative capacity with respect to new products generally, and digital ones in particular. In Spain's case, socio-demographic projections are likely to describe a double transition in the long term. On the one hand, a marked ageing effect will bring about a drop in the country's innovative capacity in adopting digital products. On the other hand, a process of a general improvement in the educational level should improve such innovative capacity. We will demonstrate which of these trends prevails in adoption and diffusion when it comes to using the internet, e-commerce and online banking, giving due consideration to the empirical evidence observed in adoption behaviour for such technology by the heterogeneous representatives presented in this paper.

In Section 2, some useful literature is reviewed which describes the methodology in the Bass model (1969). Some reading is quoted in which this model has been extended using some kind of heterogeneity, as are the papers which have been written on the diffusion of one or other kind of digital product. Section 2 also describes the socio-demographic transitions which Spain's population is likely to experience. Section 3 covers the data and econometric estimation which will determine the p and q values of the representative individuals and projections are forecast for them, taking into account the transitions mentioned earlier. Section 4 offers conclusions.

2 The bass model, heterogeneity and the digital economy

The Bass model (1969) quantifies the number of consumers who are going to acquire or use a new product or technology at a moment in time. The speed at which this happens relates to the number of innovators and imitators in the economy. Innovators are those consumers/users who adopt or buy the new product or technology irrespective of how other consumers behave. Their consumption preferences tend towards trying out products which are new, just because they are. Imitators start to consume or adopt such products when they see that other consumers (e.g. the innovators) gain utility from consuming the good, and they think that they can also gain by adopting the technology. The Bass model (1969) is represented using the following formula:

$$S(t) = \left[p + \left(\frac{q}{m}\right) N_{t-1}\right] [N - N_{t-1}] \qquad (1)$$

Where:

$S(t)$ is the number of consumers adopting the innovation in time t, N_{t-1} is the number of consumers who have adopted the innovation up to the point in time t-1 and m is the estimated potential market. Note that

$$S(t) = N_t - N_{t-1} \qquad (2)$$

N denotes the maximum number of consumers who might buy the product. The parameter p (also known as the coefficient of innovation) is the probability of an innovator adopting the product in time t. The parameter q is the coefficient of imitation, the probability of an individual classified as an imitator adopting a new product. This parameter describes a kind of diffusion of the innovation by word-of-mouth and the inter-relationship between innovators and imitators. In numerous cases of work on this, estimation of the model revealed a pattern of cumulative adoption of an innovation that traced a typical S-curve.

This model features certain conditions (Mahajan et al., 1995):

- The model applies to initial purchases and not replacements.
- It applies to general demand for a product category and not to different versions of any single product.
- Growth of demand for a new product can be delayed due to supply constraints that arise from limited production capacity.

The aim of this model is to quantify the speed at which diffusion of a new product or technology is observed. The model itself is completely deterministic and the various causal factors which would explain the diffusion are not specified. The dynamics of the model are determined by the values taken by the estimated p and q parameters for each type of good, geographical setting and each point of time estimated in the model.

Countless studies have been made since then, in which the p and q parameters are estimated for a highly diverse array of products. In a meta-analysis work, Sultan et al. (1990) use 213 models from different publications to show that the mean p and q values obtained are 0.04 and 0.30 respectively. The values obtained in the studies depend on the type of product being observed, the number of years for which data is available and the econometric technique used to estimate them.

The underlying variables in the model are hard to observe and quantify (Rogers, 1995). They nonetheless go a long way towards offering a theoretical explanation of the empirical p and q values observed in the Bass model.

These factors can be a characteristic of the consumer or external. Among the own attributes which influence potential adopters of a new innovation we may find:

- Relative advantage of the innovation or the new product.
- Compatibility with the lifestyle of potential clients and the social norms within the environment where this is pursued.
- Complexity of the innovation or new product.
- Trialability by the potential adopter and the chance to evaluate it after trying it out.

On the other hand, the external or social determinants which can speed up or slow down the adoption process may be summarised as:

- Whether the decision to adopt is taken collectively, by individuals or by a central authority.
- The communication channels used to acquire information about an innovation, whether this be the mass media or interpersonal relations.
- The nature of the social system within which the potential adopters find themselves, its norms and the degree of interconnectedness.
- The extent of change agents' promotion, development agencies, etc.

Heterogeneity in diffusion models

Subsequent developments of the Bass model (1969) further refined it with the introduction of supply-side heterogeneity. The globalisation of the economy has stepped up market competition and the innovation process has speeded up in the past few decades, most particularly in the area of digital technology (Van den Bulte, 2000). This has given rise to products being replaced by other, improved ones even before they have completed their life cycle. To incorporate this phenomenon, Norton & Bass (1987) and Bass (1995) propose an enhanced diffusion model which brings in product generations. Following this line, Pae & Lehmann (2003) find an inverse correlation between the inter-generational duration of a technology product and the coefficient of innovation, whereas this is positive with the coefficient of imitation.

On the demand side, firms use business intelligence to design commercial campaigns that target specific population segments. Even so, as Rangaswamy & Gupta (1999) note, diffusion models use aggregate data on the whole pool of potential clients who adopt a product in a given period, and ignore how different kinds of individuals can react to innovation in very different ways. Along these lines, Gatignon & Robertson (1986) claim that examples of consumer behaviour on an aggregate level in traditional diffusion models are too simplistic to provide a satisfactory explanation of the pattern of behaviour in diffusion. This is why one of the challenges in improving the Bass model is the study of diffusion behaviour according to different kinds of individuals.

The literature does not include much work involving quantification of the coefficients of innovation (p) and imitation (q) of a differentiated nature for the various types of clients, although the work that does exist has shown that the heterogeneity of potential consumers (defined using diverse criteria) is very important in explaining patterns of adoption and diffusion of new technologies (Chatterjee & Eliashberg, 1990; Van den Bulte & Stremersch, 2004; Bemmaor, 1994).

Other complementary line of work is that by Roger (1983) on the sociological aspects that relate to innovation. Several variables of a socio-economic hue (such as education, age, social status and social mobility), as well as specific characteristics of the consumer's personality (like empathy, dogmatism and rationality), can be determinants in explaining the adoption process for a technology. Other elements can also reveal themselves to be very important, especially those that relate to the individual's behavioural patterns regarding communication (social participation, exposure to the mass media, how cosmopolitan they are, etc.).

As Rogers (1983) says, innovative people correlate very closely with educational level and social status. There are several reasons that might explain this correlation. On the one hand, innovators perceive the gain to be had from innovation faster than imitators but, on the other hand, they have to assume the risk that the innovation might not be as successful as they were expecting. Thus, people with more means (those who are better educated) can afford to take the risk entailed in adopting a new technology. On the other hand, both technologies and innovative products tend to be more expensive and are more affordable for higher-income individuals. Van den Bulte & Stremersch (2004) find that the adoption process correlates very closely with income level. Since this in turn is very closely related to educational level and age, then innovation, education and age ought to correlate closely to each other. Finally, the technical features of new technologies require a certain degree of technical ability to be used, which is more easily found among those with a high educational level. To conclude, age and educational level are defining elements of the ability to innovate of both individuals and a country generally.

Diffusion models and digital technology

The internet has become established at a far greater speed than that observed for consumer durable goods, even those which are also of a technological nature, such as radio, television or cable (Rangaswamy & Gupta, 1999).

According to Scott Morton (2006), the reason for this trend lies in the combination of a whole set of factors. First, the internet is the necessary platform for consuming many other digital products, meaning that if a consumer wishes to use such digital products they must necessarily have internet access. On the other hand, internet use can double up for both social and leisure activities and as a work tool. At the same time, both using the internet and having access to the wide range of digital products and services that are marketed by using it as a platform enables these products to be purchased at keener prices than if they were bought through traditional channels, owing to the low cost of online marketing. It also allows the characteristics of goods and services to be compared quickly and conveniently. Such dynamism and the fierce competition that has been observed tend towards the life cycle of these products being increasingly shortened, which encourages the whole innovation process.

In terms of the Bass model (1969), digital products might bring about certain changes in the parameters estimated in them compared to traditional products (Rangaswamy & Gupta, 1999). More specifically:

- The potential market for a product or innovation (m) increases and could be larger. Access to many digital services transcends local or national boundaries and spreads throughout the global market.
- The coefficient of imitation (q) is expected to rise. The ease of information exchange over the web, digital marketing and more efficient word-of-mouth relay via chats and social networks should favour quicker imitation in consumption than has previously been the case.

- The coefficient of innovation (p) could be higher. Given that the digital medium offers the client more information and offers the chance to access product demonstrations, innovators will have more facilities to access new products and technologies.

Table 2.1
Different estimated p and q coefficients for digital products

	Interval studied	p	q	Country	Study
Cable TV	1981-1994	0.100	0.060	USA	I&VDB
Mobile phone	1986-1996	0.008	0.421	USA	I&VDB
PC	1982-1988	0.121	0.281	USA	I&VDB
Mobile phone	1986-2006	0.004	0.230	USA	WV
Mobile phone	1986-2007	0.001	0.700	Argentina	WV
Internet	1993-2006	0.014	0.160	USA	WV
Internet	1993-2007	0.007	0.430	Argentina	WV
Broadband internet	1999-2007	0.024	0.470	USA	WV
Broadband internet	2001-2007	0.004	0.690	Argentina	WV
Internet	2003-2013	0.022	0.121	Spain	OR
E-commerce	2003-2013	0.013	0.222	Spain	OR
Online banking	2003-2013	0.009	0.160	Spain	OR

Source: Lilien & Van der Bulte (1999) (I&VDB); Weissmann (2008) (WV); Own research (OR)

Other work such as that carried out by Correa et al. (2015) and Pérez Hernández & Sánchez-Mangas (2011) justifies using age and educational level as determining factors in adopting and using new products within information and communications technology (ICT) in Spain.

Demographic and socio-economic dynamics

Socio-demographic variables have proved very significant in explaining adoption behaviour, yet they have seldom been employed in the Bass model as explanatory variables of the speed of adoption in it.

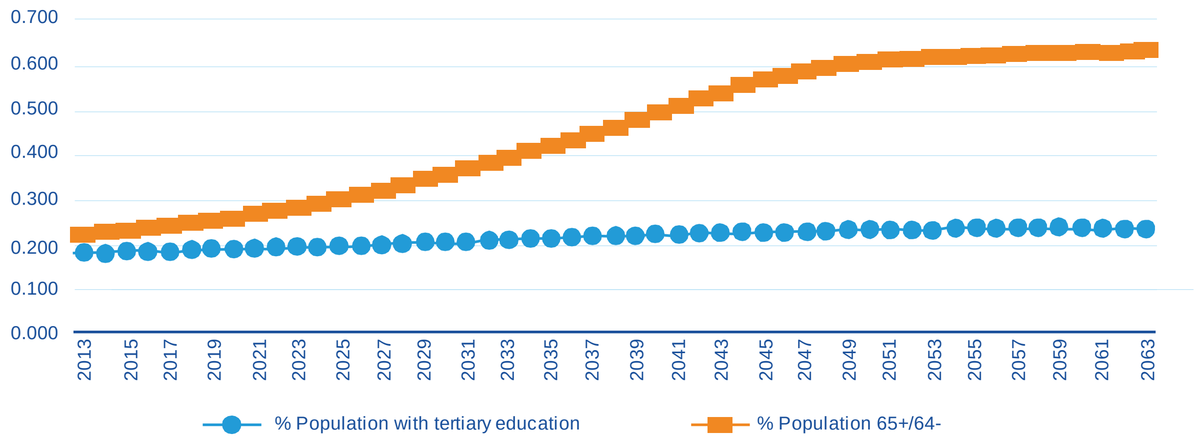
In this paper, we propose segmenting certain types of individuals who might exhibit different innovative and imitative behaviour according to the characteristics.

The idea behind segmentation of this kind is that the imitators in each group mainly inter-relate with individuals in the same classification as themselves. For example, if we divide the life-cycle of a specific generation into three phases (education, working life, retirement), students spend most of their time with other students with the same educational level as themselves. People of working age mix for more hours of the day with work-mates of the same educational level. Finally, population cohorts of retirement age normally interact with those in their own peer-group. The stronger links within groups might cause them to have differing coefficients of imitation (q). On the other hand, the innovation component (p) might be affected negatively according to the individual's age. Thus, in this paper, we raise the issue of whether age (life-cycle phase) and educational level might be elements that mark out differing p and q values and, therefore, a different speed of adoption (of digital goods and services in the case that concerns us here).

For the coming years, the projections for Spain's population show two clearly defined transitions which will significantly alter its composition. The population ageing process that will be observed in the future will give rise to an increase in the percentage of people of retirement age in relation to the other cohorts. As Figure 2.1 shows, the population aged 65 or over should move from equalling 22% of the population under 65 to 63% in 2060.

The next transition which will be experienced by Spain's population is the rise in the general educational level. The generation that is currently completing its studies is reaching a level of educational attainment which is higher than in the case of older generations. Assuming that future generations achieve the same educational level as the younger generations at the moment, the percentage of people over 16 who are likely to have reached university level will have risen from 17.7% today to 23.5% in 2060 (see Figure 2.1).

Figure 2.1
The educational and demographical transition in Spain



Source: National Statistics Institute and BBVA Research

This shift in the heterogeneous component of the potential market could cause the innovation and imitation components of Spain's population to vary in the future.

3 Data and econometric model

The data

The data used in this document come from the Equipment & Use of ICT in Households (TIC-H) Survey by the National Statistics Institute (INE). The survey has been conducted annually since 2002, with the fieldwork carried out in the second quarter of each year (for further details see INE, 2014).[1]

The available information covers usage and access with regard to the various different ICT products in Spanish households and, more specifically, the use made of internet-based digital services (e.g. e-commerce and online banking).

Whereas the use of e-commerce can be analysed via a question in the questionnaire which does not involve time constraints, the descriptions for internet and use of online banking depend on time periods. In the questionnaire associated with the survey, respondents are asked whether they have used the internet at least once in the past three months, as they are also asked in the cases of online banking and financial activities such as buying shares, insurance policies and similar products.

The data that will be used in this paper takes in 2003-14, for which there is information for all the variables concerned. The target population is people who are over 16.

Eight different groups of consumers are established according to age and educational level as of 2003 and in line with the life-cycle phase which the particular population cohort is going through that year, as is illustrated in Table 3.1.

The typical age for secondary education in Spain is from 16 to 18, and from 19 to 25 for university.[2] The second life-cycle phase is framed in terms of typical working lives (16-64 for primary education, 19-64 for secondary education, and 26-64 for university education). The third phase in the life-cycle begins with retirement for all those over 64.

Table 3.1
Groups of consumers by age and educational level in 2003

Group	Age band	Educational level
1	16-18	Secondary
2	18-25	University
3	16-64	Primary or below
4	19-64	Secondary
5	26-64	University
6	Over 64	Primary or below
7	Over 64	Secondary
8	Over 64	University

Source: BBVA Research

1 This survey follows the recommendations made by the European Union's Statistics Office (Eurostat).
2 The typical age for primary education (6-15) is not represented in the sample in the same way and requires special treatment, separately from the rest of the population.

Based on this classification for 2003, the age limits are shifted from year to year as more surveys from more recent years are used. This way, the idea is to monitor generations of individuals and observe developments in the adoption of the internet, e-commerce and online banking.

Using reasoning that is similar to that proposed by Correa et al. (2015) and Pérez-Hernández & Sánchez-Mangas (2011), the population being studied is filtered using a tree for the ICT adoption process. Thus, people who use e-commerce and/or online banking services must have previously stated that they have used the internet. Thus the potential market studied in the case of internet use is broader than the population which might engage in e-commerce and might use online banking services.

The econometric model

This is a distribution function of adoption as a function of time, F(t), such that F(0) = 0 and f(t) is the associated density function. The central proposition of the Bass model is based on the assumption that the likelihood of adoption at a point in time t given that adoption has not yet occurred [f(t)/(1-F(t))] is equal to a parameter p (coefficient of innovation) plus a parameter q (coefficient of imitation) which is multiplied by F(t), the cumulative fraction of people who have adopted the technology at a point in time t:

$$\frac{f(t)}{1-F(t)} = p + qF(t) \qquad (3)$$

An additional assumption in the model is that F(t) = mN(t), where m is another parameter of the model (that relates to the ultimate potential number of people who might adopt) and N(t) reflects the cumulative number of people who have adopted in the period t.

The modelling process for the diffusion of new products is explained in the study made by Mahajan et al. (1995). In a context that relates more closely to innovation diffusion processes, Kijek & Kijek (2010) suggest four proposals for estimation of the Bass model. For our purposes here, two of these are followed up, namely the proposal of initial Ordinary Least Squares estimation (OLS) and also that of final estimation using Non-Linear Least Squares (NLLS).

The OLS option is based on a discrete time version of the expression given above:

$$N(t) - N(t-1) = \beta_0 + \beta_1 N(t-1) + \beta_2 N^2(t-1) + u(t) \qquad (4)$$

where u(t) represents the disturbance in the model and each of the parameters in the model (β_0, β_1, β_2) has a relationship with the key terms in the Bass model: β_0 = pm, β_1 = (q - p), β_2 = - q / m. The number of periods (t) runs from 2003 to 2014.

OLS estimation can produce results that are inconsistent with the true meaning of the parameters. It can give rise to values that do not belong to the set of real numbers, or negative or not very robust values (given the true definition of p and q, while their values must belong to the interval (0,1) and the sum of both of these must be no greater than one) when the number of observations available to carry out the regression is small.

The alternative that allows such limitations to be overcome is NLLS estimation. This kind of estimation is based directly on the original formulation of the Bass model, where a result for the number of people adopting between t-1 and t is obtained by solving the differential equation upon which it is based:

$$N(t) - N(t-1) = \frac{m - \frac{p(m-N_0)e^{-(p+q)t}}{p+\frac{q}{m}N_0}}{1+\frac{\frac{q}{m}(m-N_0)e^{-(p+q)t}}{p+\frac{q}{m}N_0}} - \frac{m - \frac{p(m-N_0)e^{-(p+q)(t-1)}}{p+\frac{q}{m}N_0}}{1+\frac{\frac{q}{m}(m-N_0)e^{-(p+q)(t-1)}}{p+\frac{q}{m}N_0}} + u(t) \quad (5)$$

where u(t) is the disturbance in the model and parameters p, q and m can be directly estimated. N_0 is the cumulative number of people adopting at the initial time. In the estimation process, the values obtained in the process of OLS estimation are generally set up as initial values for the NLLS estimation process.

4 Results for digital technology adoption in Spain

As we mentioned earlier, for each kind of digital product (internet, e-commerce and online banking) we estimate the coefficients of innovation (p) and imitation (q) using the OLS and NLLS estimator for each grouping described according to Table 3.1.

4.1 Estimation of the coefficients of innovation and imitation for heterogeneous agents

In the results obtained via OLS estimation, the regressions obtained for the estimated β_0, β_1, and β_2 parameters do not allow us to arrive at values with minimum conditions for p and q ($p, q \in R$) (see Annex A). The results point to the unreliable nature of OLS estimates compared to NLLS estimates, bearing in mind that, by definition, parameters p and q belong to the interval (0,1) and that the sum of both parameters belongs to that same interval. Most of the OLS results do not fall within this interval.

The results obtained are in line with those observed by Schmittlein & Mahajan (1982), who ponder the suitability of using OLS as an estimator, due to problems of multicollinearity of N(t-1) and $N(t-1)^2$ in Equation 2. Moreover, the results do not provide the standard errors of the estimated p and q parameters. There can also be bias because discrete time series are being used to estimate a model that should be continuous.

In the case of the results obtained using NLLS, the figures satisfy the conditions and are statistically significant. The results using NLLS are far more consistent and are given below.

Adoption and diffusion of internet use

A large portion of digital products which are offered to citizens necessarily require consumers to be internet users. Adoption and diffusion of this kind of product is thus contingent upon there having been prior diffusion of internet use.

In Spain's case, Table 4.1 offers estimates for p and q for eight groups of people that have been obtained using the two estimation methods examined and incorporating internet use as a study variable. The estimates for p and q using NLLS that are shown also include the associated standard deviations in brackets.

Table 4.1
Estimates for p and q parameters using NLLS – internet

NLLS	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6	Group 7	Group 8	Total
p	0.048 (0.004)	0.022 (0.001)	0.009 (0.004)	0.019 (0.003)	0.025 (0.003)	0.000 (0.000)	0.000 (0.000)	0.023 (0.008)	0.022 (0.002)
q	0.133 (0.035)	0.193 (0.016)	0.320 (0.055)	0.114 (0.020)	0.082 (0.016)	0.095 (0.020)	0.071 (0.011)	0.092 (0.043)	0.121 (0.013)

Source: BBVA Research

The estimates suggest that the coefficients of innovation (p) are higher for young people of an age when they typically receive education than for the other population cohorts given the same educational level, except in the case of university education, where the coefficients are very similar among all the age groups taken into account (groups 2, 5 and 8).

The coefficients of innovation (p) are also higher given the same age for university education compared to other educational levels within the middle age interval, and the difference is especially marked in the higher age bracket. This relationship is not, however, satisfied among the younger groups.

In the case of the coefficient of imitation, behaviour differs substantially and no clear general pattern is discernible. The youngest individuals who study at university level (group 2) have a higher coefficient of imitation than those who are in secondary education. Nonetheless, within the intermediate age band there is an inverse correlation between this coefficient and the educational level, which is especially high among people with a primary educational level or below. Among the older population, there are no marked differences in terms of educational level (groups 3, 4 and 5).

Figure B.1 in Annex B shows the fit between the original series and the estimated series for internet adoption based on the estimates in Table 4.1. In addition, the confidence intervals for the estimated series are included at a level of 95 percent. The results for the fit are generally quite satisfactory, with the fit lying within the confidence intervals in most cases. The greatest difficulty in producing better fits appears among the groups that are educated to primary level or below, which exhibit greater volatility compared to the other series. This group shows a more erratic pattern in terms of internet use and produces greater width in confidence intervals.

This result confirms that diffusion of internet use has been faster among the higher educational levels and the middle age group of the population due to their higher coefficient of innovation.

Older people who lack a university education have shown a lower degree of internet use adoption, due to the fact that they exclusively rely on their imitative capacity. It is only now that they are displaying a greater presence in terms of this medium, notably lagging behind the rest.

Adoption and diffusion in e-commerce use

For the case of diffusion of e-commerce use, the potential population is the universe of individuals who say they use the internet in the survey.[3]

Table 4.2 shows the estimates obtained for the eight groups via NLLS estimation for p and q parameters considering e-commerce use as the study variable. The associated standard deviations are given in brackets.

Table 4.2
Estimates of p and q parameters using NLLS – e-commerce

NLLS	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6	Group 7	Group 8	Total
p	0.016	0.013	0.007	0.012	0.016	0.000	0.009	0.014	0.013
	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.000)	(0.005)	(0.007)	(0.002)
q	0.259	0.272	0.412	0.220	0.187	0.155	0.494	0.171	0.222
	(0.053)	(0.035)	(0.061)	(0.036)	(0.045)	(0.104)	(0.113)	(0.085)	(0.036)

Source: BBVA Research

3: The source of these figures is reasonable because we have not come across any e-commerce users who say they do not use the internet.

In general, estimates of the coefficient of innovation for e-commerce use are smaller than those observed for internet use (except in group 7, although the difference is not particularly great). One of the factors which might account for this smaller coefficient of innovation in e-commerce is that the decision by innovators to adopt a new product involves weighing the relative benefit of adopting it against the risk of being a pioneer in using it. Using e-commerce in itself entails a transaction risk of fraud of various kinds. It is understandable that certain innovators who use the internet might view this compromise as unsatisfactory and would not be innovators in using e-commerce.

Within each phase of the life cycle (except receiving education) the coefficient of innovation (p) rises with the educational level attained.

In the case of the coefficient of imitation, the figures are higher as regards online shopping than for internet use, which could indicate that consumer wariness is initially higher, either due to a lack of awareness about the product or because they feel greater aversion to the risk of using it. Word-of-mouth explanation of the pros and cons in the imitation process might mitigate suspicion regarding the risks of using it.

The results for the coefficient of imitation follow a behavioural pattern by age and educational level that is similar to that shown in internet use. Younger people studying at university level have a higher coefficient than those who study at secondary level. On the other hand, there is an inverse correlation between this coefficient and educational level among the set of people of working age, which is especially high among people educated to primary level or below. The most notable difference occurs among the over 64s, where the group in secondary education exhibits a very high coefficient compared to the other educational levels.

Figure B.2 of Annex B offers a comparison between the original series and the estimated series for e-commerce adoption based on NLLS estimation. It also shows the confidence intervals for the series estimated at the 95 per cent level. The results reveal that the model's fit is generally very satisfactory. Once again, there is some difficulty in producing results that are similar to the real figures for the groups with a primary education or lower, which display greater volatility compared to other educational levels for each age interval. In particular, the over 64s with a primary educational level or lower show more erratic behaviour in terms of online shopping, which gives rise to greater width in confidence intervals. By age band, the over 64s show the greatest variability and smallest presence in this activity, which supports the conclusions derived from the estimates of the coefficients.

Adoption and diffusion in online banking use

With respect to online banking, Table 4.3 shows the estimates of the p and q parameters for the eight groups of consumers using NLLS. As with the previous tables, Table 4.3 gives the standard deviations in p and q estimates in brackets.

Table 4.3
Estimates of p and q parameters using NLLS – online banking

NLLS	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6	Group 7	Group 8	Total
p	0.011	0.008	0.003	0.005	0.010	0.000	0.009	0.028	0.009
	(0.004)	(0.001)	(0.005)	(0.003)	(0.004)	(0.000)	(0.006)	(0.010)	(0.001)
q	0.312	0.309	0.406	0.142	0.104	0.025	0.190	0.109	0.160
	(0.071)	(0.014)	(0.080)	(0.021)	(0.019)	(0.056)	(0.110)	(0.074)	(0.013)

Source: BBVA Research

In the case of the NLLS estimates, the figures satisfy the conditions but not all the groups show estimates statistically different from zero, as occurs with the p parameter in groups 3 and 7, which refer to people educated to secondary level who are in the middle and higher age categories. In the case of the q parameter, the absence of statistical significance is focussed on the older population segment (groups 6, 7 and 8).

The estimates of the coefficient of innovation for online banking use are smaller than those observed with regard to internet use, except for group 8, although the differences are not very great. This conclusion suggests that the use of online banking services might require a certain prior additional knowledge of a financial nature which stands in the way of the innovation process relative to internet use.

Compared to online shopping, the estimates for online banking are either smaller or the same, except for group 8. It could be that online banking might present an even greater risk of fraud than e-commerce, on top of also calling for financial knowledge which certain innovators (who do engage in online shopping) do not possess.

The estimated coefficients of innovation for young people compared to the others are less than in the previous cases, perhaps due to a lower level of financial knowledge or less of a need to carry out financial transactions. A correlation is also apparent between the educational level attained and the coefficient of innovation in the working life phase and in the retirement phase.

The difference in coefficients of innovation among educational levels is smaller as the risk of using a certain product increases (e-commerce and online banking). An increase in the risk of using a digital product brings down the level of innovation and reduces the differences in the coefficient of innovation among educational levels.

The case of the coefficient of imitation (as with online shopping) reveals that for some this risk product needs word-of-mouth to cause it to be adopted. This relative aversion to the risk of using this type of product is greater among groups educated to primary level. Therefore, the coefficient of imitation decreases with the educational level over all phases of the life-cycle.

Figure B.3 of Annex B shows the comparative analysis between the original series and the estimated series in adoption of online banking based on the NLLS estimation process. Confidence intervals are also included for the estimated series at the 95 percent level.

As occurred with the other two variables of interest, the groups with a primary or lower educational level show greater volatility compared to other educational levels for each age band. Moreover, the over 64s show a more inconsistent pattern in online banking, which is due to the relatively small number of observations for them and this result backs up the conclusions drawn from the estimates of the coefficients.

4.2 The effects of the demographic transitions on the coefficients of innovation and imitation in the long term

As we have seen in the previous sub-sections, the Spanish population will experience two very marked socio-demographic transitions. On the one hand, there will be a process of population ageing, where the population cohorts of retirement age will lift their absolute and relative weights in relation to the population as a whole. On the other hand, there is the gradual increase in the population's level of qualifications, whereby more highly qualified new generations eventually replace less qualified older generations.

In the previous sub-sections we have observed three broad trends in estimation of the coefficients of innovation and imitation.

1. The coefficient of innovation rises with the educational level and decreases with the individual's age.
2. The coefficient of imitation decreases with the educational level and decreases with age within the primary education category. For the other ages this is not well-defined.
3. The coefficient of innovation decreases the higher the risk component embodied in the product that is consumed, or to the extent that it requires specific knowledge to be consumed (financial knowledge).

This evidence leads us to ask ourselves what effects the socio-demographic transitions noted earlier would have on the ability to innovate and imitate for a country such as Spain.

In Table 4.4 we can observe the change between 2014 and 2050 in the values that would be taken by the coefficients of innovation (p) and imitation (q) when we only take into account the population ageing effect.[4] In the case of innovation, the greatest effect of a decrease in the ability to innovate can be observed in internet diffusion (25 percentage points, pp), followed by e-commerce (21.7pp) and online banking (12.7pp). The falls in the coefficient of imitation would be 5.6pp for internet diffusion, 2.8pp for e-commerce and 14.8pp in online banking.

Table 4.4
Population ageing effect

	p (weighted mean)			q (weighted mean)		
	2014	2050	2050/2014	2014	2050	2050/2014
Internet	0.015	0.011	0.749	0.130	0.123	0.944
E-commerce	0.010	0.008	0.783	0.241	0.234	0.972
Online banking	0.0054	0.0047	0.873	0.155	0.132	0.852

Source: BBVA Research

The effect that would be exerted on the innovation component (p) by the improvement in the population's educational level would be a rise of 8, 15.7 and 38pp for internet, e-commerce and online banking respectively. Meanwhile, for the coefficient of imitation (q) there are mixed results. On the one hand, the coefficient of imitation

4: The total p and q figures for 2014 do not match the totals in Tables 4.1, 4.2 and 4.3 because the latter are for a global estimate using NLLS, whereas those in Tables 4.4, 4.5 and 4.6 are constructed as weighted means using the population for 2014 in the projection.

as regards internet use would drop by 6.4pp, whereas it would increase by 11.4 and 7.4pp for e-commerce and online banking (see Table 4.5).

Table 4.5
Education transition effect

	p (weighted mean)			q (weighted mean)		
	2014	2050	2050/2014	2014	2050	2050/2014
Internet	0.015	0.016	1.081	0.130	0.122	0.936
E-commerce	0.010	0.012	1.157	0.241	0.268	1.114
Online banking	0.005	0.007	1.380	0.155	0.167	1.074

Source: BBVA Research

Finally, the combined effect of population ageing and the improvement in the educational level yields contrasting results. On the one hand, the population ageing effect prevails over the educational effect because the coefficient of innovation falls 10.8pp in the period. On the other hand, the coefficient of imitation would show a declining trend, dropping by 15pp. Thus the course taken by internet adoption will take the form of a reduction in the rate at which this happens in the coming years. This is worrying, because internet adoption is a necessary condition for using and consuming a broad range of digital products and services, and this situation does not bode well for innovation or economic growth.

Table 4.6
Total effect

	p (weighted mean)			q (weighted mean)		
	2014	2050	2050/2014	2014	2050	2050/2014
Internet	0.015	0.014	0.892	0.130	0.111	0.850
E-commerce	0.010	0.011	1.089	0.241	0.296	1.229
Online banking	0.005	0.009	1.626	0.155	0.162	1.046

Source: BBVA Research

On the other hand, in the case of adoption of e-commerce and online banking, the prevailing effect will be the improvement in the educational level, since the coefficient of innovation would rise by 8.9 and 62pp respectively and the coefficient of imitation would also rise, by 22.9 and 4.6pp respectively. These results are consistent in that the improvement in the educational level and certain areas of specific knowledge (such as regarding financial matters) are key to adoption when it comes to using particular digital products (e-commerce and online banking) which entail certain risks when using them or which require specialist knowledge. The trend in the next few years will be to speed up the adoption process for e-commerce and online banking.

5 Conclusions

This document incorporates several elements that are new in the literature on innovation and diffusion of new technologies. Following the Bass model (1969), we quantify the innovation (p) and imitation (q) components for an assortment of different individuals who are classified according to the life-cycle phase which they are in (education, working life and retirement) and their level of educational attainment. The results obtained show that:

- In the future, studies which use the Bass model could be improved by segmenting target populations to control for heterogeneity.
- The coefficient of innovation rises with the educational level and decreases with the age of individuals.
- The coefficient of imitation decreases with the educational level and decreases with age in the primary education category. For the other ages, this is not clearly defined.
- The coefficient of innovation decreases to the extent that the product consumed incorporates a component which involves greater risk or requires specific knowledge to be consumed (financial knowledge).

The next innovative element in the paper is that there is measurement of the future effects which a different socio-demographic mix within the Spanish population might have. This would be brought about by both the population ageing process and the transition towards an improved educational level among the population.

The population ageing effect could cause a decrease between 2014 and 2050 in the coefficients of innovation of 25pp for internet diffusion, 21.7pp for e-commerce and 12.7pp for online banking. At the same time, the coefficient of imitation would come down by 5.6pp, 2.8pp and 14.8pp respectively.

The effect of an improvement in the educational level would bring about a rise in the coefficient of innovation by 8.1pp for internet diffusion, 15.7pp for e-commerce and 38pp for online banking diffusion. On the other hand, the coefficient of imitation in the primary education category would drop by 6.4pp, while it would rise by 11.4pp for e-commerce and 7.4pp for online banking.

The combined effect of both transitions would mean that in the case of internet diffusion the ageing effect would prevail, bringing down the coefficient of innovation for this by 10.8pp and the coefficient of imitation by 15pp. On the other hand, for e-commerce and online banking diffusion the improvement in the educational level would predominate, lifting the coefficients of innovation for e-commerce and online banking by 8.9pp and 62pp respectively. At the same time, the coefficients of imitation would rise by 22.9pp and 4.6pp respectively.

The effects that arise from these dynamics mean that we might witness a steady trend of a reduction in the diffusion of internet use, while diffusion increases for e-commerce and online banking use.

The lessons as regards economic policy that can be drawn from this paper tell us that even if governments can do little to change the population ageing process, they can act with regard to the educational component, with respect to both the young and older people. Future papers should study how improving the quality of formal education (above all in digital matters) can raise a country’s coefficient of innovation to the extent that this offsets the effect of a loss of competitiveness due to population ageing.

A Annex

OLS estimates

This annex gives the estimates of the coefficients of innovation (p) and imitation (q) for representative individuals using OLS. The process of deriving standard deviations in OLS estimation is a very tricky proposition, given that the estimates of the parameters of interest are arrived at by solving a multiple equation system.

Table A.1
Estimates of p and q parameters using OLS

Internet

OLS	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6	Group 7	Group 8	Total
p	1.220	-0.079	-0.262	-	0.964	-0.188	0.602	-2.115	-
q	-0.814	0.658	1.169	-	-0.879	0.840	-0.396	3.492	-

E-commerce

OLS	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6	Group 7	Group 8	Total
p	0.060	0.139	0.054	-	-	1.672	0.305	0.155	-
q	0.650	-0.045	0.692	-	-	-0.156	0.416	0.746	-

Online banking

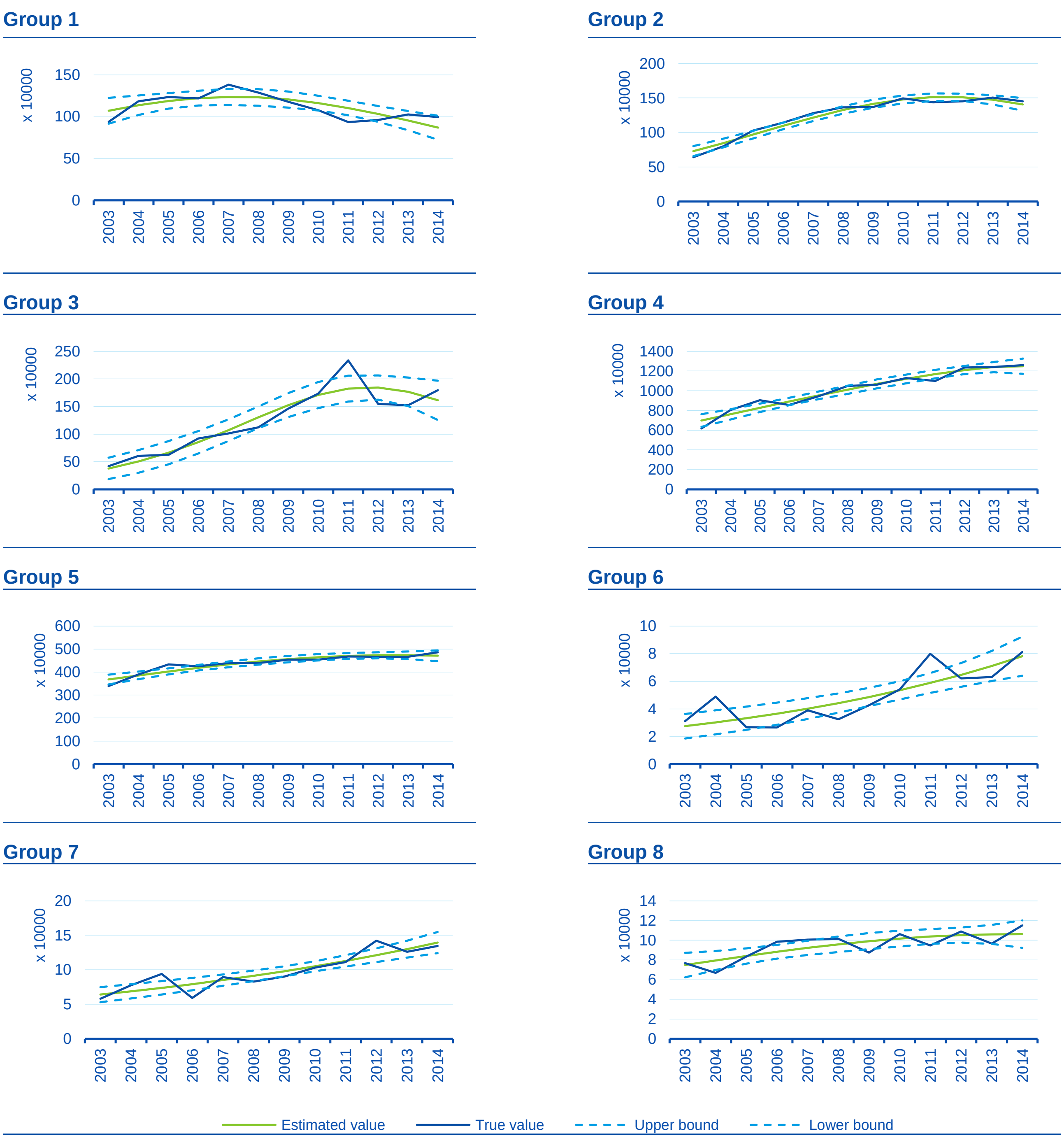
OLS	Group 1	Group 2	Grup 3	Group 4	Group 5	Group 6	Group 7	Group 8	Total
p	-0.007	0.000	-0.281	0.004	-	0.713	-0.072	-0.951	-
q	0.921	0.486	1.526	0.117	-	0.550	1.146	2.356	-

Source: BBVA Research

B Annex

Comparative figures for original vs. estimated series using NLLS

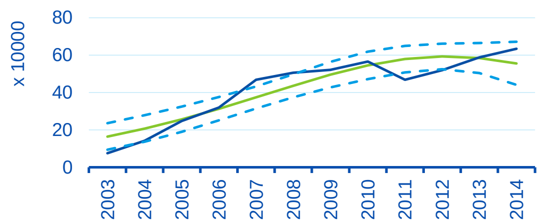
Figure B.1
Comparison of adopters for internet



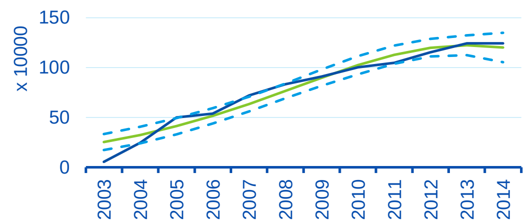
Source: BBVA Research

Figure B.2
Comparison of adopters for e-commerce

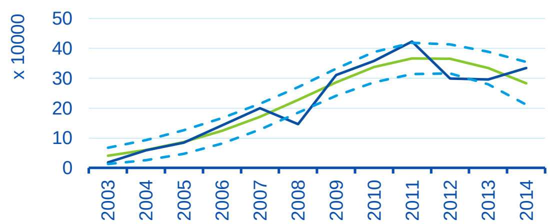
Group 1



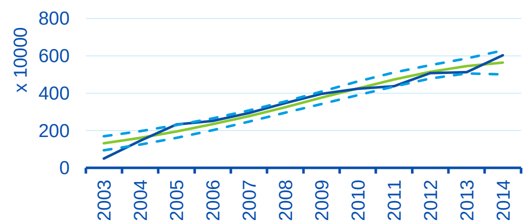
Group 2



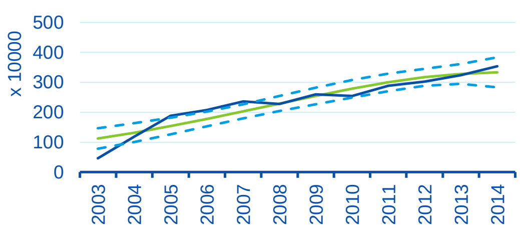
Group 3



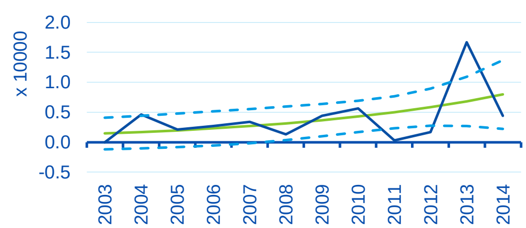
Group 4



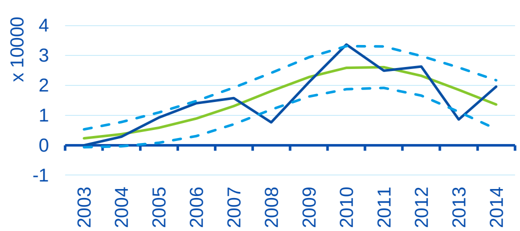
Group 5



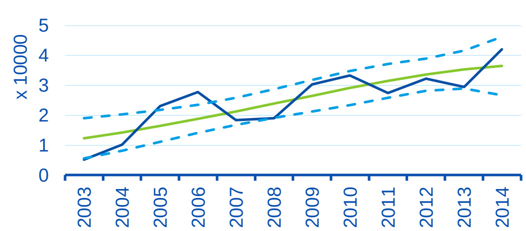
Group 6



Group 7



Group 8



Estimated value — True value — Upper bound — Lower bound

Source: BBVA Research

Figure B.3
Comparison of adopters for online banking

Source: BBVA Research

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