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Analysis of the behaviour of the clients assisted and sales variables in the different phases of the product life cycle

Aida Galiano and Vicente Rodríguez
International University of La Rioja, Madrid, Spain, and
Manuela Saco
CEU San Pablo University, Madrid, Spain

Abstract

Purpose – The Bass model was created to analyse the product life cycle (PLC) in order to help sales and marketing departments in their business decision making. The purpose of this paper is to analyse the diferences between the clients assisted and sales variables, to discover which of the two variables is the more useful for the estimation of the PLC phases through the Bass model, thus aiding the managers of company sales and marketing departments.

Design/methodology/approach – In this research, the authors analysed the 223,577 clients assisted by a nationwide network of car dealerships, who acquired 36,819 vehicles, during a 24-month period. In the analysis, the Bass model was applied to define the PLC phases; and nonlinear regression models were used to carry out the estimations.

Findings – The results show that more consistent estimates of the PLC phases are obtained from the clients assisted variable. This work has theoretical and practical implications that can help business management.

Research limitations/implications – The most remarkable thing about this research is that we have shown that the functionality of the clients assisted variable is greater than the sales variable for the Bass model and, therefore, for PLC estimation.

Practical implications – The results of this research are very useful, since they allow marketing decision makers to obtain more consistent estimations of the PLC phases using the Bass model and the clients assisted variable. This is based on the fact that the use of this variable helps to detect if there is any deficiency in the design of the marketing strategy when the client does not make the purchase.

Social implications – The data on clients assisted are as easily available to companies as sales data. However, the use of this variable improves PLC analysis and this allows an improvement in company forecasting. Thus, making the clients assisted variable a tool to strategically plan investments in innovation and marketing would reduce uncertainty in business management.

Originality/value – The purpose of this paper is to analyse the diferences between the clients assisted and sales variables, to discover which of the two variables is the more useful for the estimation of the PLC phases through the Bass model, thus aiding the managers of company sales and marketing departments.

Keywords Consumer behaviour, Time series, Automotive, Bass model, Life product cycle

Paper type Research paper

1. Introduction

The product life cycle (PLC) is an important concept in the product marketing process, for consumer behaviour and in adapting to the changes that occur in the environment and in the competition. These changes condition the design of marketing strategies and, therefore,

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knowledge of the behaviour of the market can contribute to reduce uncertainty and improve marketing decisions (Briede-Westermeyer *et al.*, 2016, p. 622); hence, the importance of PLC analysis for marketing and sales departments. Miquel and Mollá (1982) pointed out that "the recognition of the existence of the PLC highlights the need for product innovation by companies. Therefore, an important element in planning the company´s innovation strategy is the position of its products in reference to the PLC and the form it adopts".

PLC analysis is of utmost importance for companies, since it allows them to use forecasting as a tool to strategically plan investments in innovation and marketing; therefore, PLC knowledge and development represents a future scientific challenge. Saffo (2007) supports this … "the art of forecasting is in identifying an S curve when it begins to emerge, well before its inflection point". In addition, it has been proven (Qualls *et al.*, 1981; Shu *et al.*, 2015) that sales data for the most recent innovations show a progressive shortening of life cycle duration, especially of the product introduction and growth phases.

Some authors (Aguilar *et al.*, 2012, Rink and Swan, 1979, Fu, 2009) noted that PLC phases differ from the normal "*S*" form model widely used in the literature. Sales data, currently the commonly adopted performance measurement in PLC analysis, may not be the most consistent variable because they are affected by certain economic phenomena, such as general price increases in the economy (inflation) or by variations in relative prices (in some products in respect to others). Spain is one of the member countries of the OECD where disposable income is significantly affected by tax and redistributive policies, especially in times of expansion, where these have a strong social component (Camacho and Galiano, 2009).

In this regard, some studies (Rodríguez Escudero, 1996; Aguilar *et al.*, 2012; Muñiz Ferrer, 2008, Mahajan *et al.*, 1995) corroborated that the sales variable is not the best measurement. They argued that this is due to it being affected by economic and sociodemographic variables, as well as the evolution of complementary markets; and they point out the inadequacy of long-term PLC forecasts based on the sales variable, given the extreme sensitivity of the sales curve to initial conditions. It can be inferred from this that there is a possibility that anomalous behaviour in some PLC cases is caused by the influence of external (to the company) macroeconomic phenomena, but that these can strongly affect the sales variable and, therefore, PLC analysis.

The objective of this study is to study the development of the life cycle of a durable consumer product in the Spanish market. The analysis of the PLC is intensified, differentiating between the customers assisted and sales variables, with the purpose of developing a business decision methodology that allows us to distinguish between the uses of both variables.

In this context, we consider that this study could be a significant opportunity within the scientific landscape and an ambitious challenge to analyse the influence of the sales and customers assisted variables in the PLC phases in the Bass model. We consider that the originality of the use of the clients assisted variable, which opens up a new research line, gives this research fundamental importance. Our main methodological contribution is the use of the clients assisted variable, which has previously not been studied in this context, in the Bass model. Historically, only the sales variable has been consistently used.

This leads us to formulate the following question: can the clients assisted variable constitute an efficient and consistent substitute for the sales variable in estimations of the PLC?

2. Theoretical framework

2.1 PLC

We have conducted a thorough review of the PLC and Bass model (which has a predominant role in dating the PLC phases) literature, finding that the studies all refer to sales volume as the single analytical variable. The most relevant articles that use the sales variable for PLC and Bass model analysis are summarised in Table I.

Variable employed	Scope of application	Research objective	Study limitations	Sources
Sales	Sales of 314 industrial vendors	New product launches	First years of product launches	Fu (2009)
Sales	Sales of technological products	PLC prediction model	The use of historical data	Orbach and Fruchter (2014)
Sales	Sales of 29 brands	Introduction into new markets	Little depth on the product PLC	Shankar *et al.* (1999)
Sales	Sales of new products and PLC	PLC analysis	No benefits are defined in the relation between both variables	Suomala (2004)
Sales and price	Sales and price evolution	PLC analysis	Supply and demand evolution	Kaldasch (2015)
Sales	Analysis of the sales of 8 products in 9 countries	PLC analysis	Analysis of consumer durables	Palacios (2013)
Sales	Potential clients' purchase intentions	New product launches	Absence of analysis of purchase decisions	Briede-Westermeyer *et al.* (2016)
Sales	Sales of 3 products	PLC analysis	Absence of analysis of the influence of habit	Ratcliff and Doshi (2016)
Sales	Sales evolution over the course of time	New product launches	Absence of market size analysis	Cetinkaya and Thiele (2016).
Sales	General Electric sales	Conversion rates	Analysis of sales in a market	Ledingham *et al.* (2006)
Sales	Mobile phone sales and internet access	Communications and digital economy sector	Absence of patterns of adoption between countries	Weissmann (2008)
Sales	Sales in the electrical energy sector	PLC	Absence of business implications	Hachula and Schmeidel (2016)
Sales	Analysis of customer product fatigue	PLC analysis	Homogenous population Inability to take account of cross sales	Wu *et al.* (2015)
Sales	Apparent consumption	Analysis of the development of the PLC of consumer durables	Estimation of sales due to lack of data	Polo (1983)
Sales	Sales estimate real diffusion curve	Analysis of sales diffusion in different countries	Poor model adjustment in some countries	Zhu *et al.* (2017)
Sales	Unit product sales in the industrial sector	PLC measurement	Influence of macroeconomic variables on sales	Aguilar *et al.* (2012)
Sales	PLC approximation theory	Confluence between Chaos Theory and PLC	Sensitivity of the sales curve used in PLC	Rodriguez Escudero (1996)
Sales	Sales simulations and inventory management	Forecast of fashion industry demand based on the Bass model and Newsvendor	Use of theoretical models	Spragg (2017)

Table I.
Summary of the revision of the theoretical framework of the use of the sales variable for the analysis of PLC and Bass model

From the discussion above, and this review, where we found that sales was the only variable used, the authors argue that it is important for companies to use not only sales performance to understand the status of their products. As we propose in this study, they can use other types of performance parameters when studying PLC phases and, by extension, in the Bass model, such as the number of clients assisted.

The PLC has historically been defined as the evolution of sales of a product during the time it remains in the market (Levitt, 1981). The PLC concept can also be applied to different levels of product aggregation. Three basic levels are used: the product class, the particular form of the product and the specific brand. Some authors consider that it is necessary to define the product according to product class, since this relates more to the different ways of satisfying a need (Lambkin and Day, 1989). Other authors (Lambin, 1995) advocate the product form, which is more closely related to its technological features and its market and, finally, there are authors who argue that analysis should be undertaken at the brand level, because the company holds control over the brand and over its strategy (Ryan and Riggs, 1996). It can be said that a certain scientific approach has been developed on the effectiveness of the sales variable in PLC analysis and for the company (Underhill, 2006, Ledingham *et al.*, 2006, Fu, 2009).

The PLC is represented graphically and determined from when it appears in the market until it is removed from the market (Clifford, 1965). Aguilar *et al.* (2012) conducted a study of the life cycles of three products based on a logistic model of population growth as a PLC measurement tool. In addition, they obtained the inflection points of the curves. These points could be used as tools for making strategic decisions about the product and can be the keys to deciding when to launch technological innovations, make investments and execute marketing strategies. Along these same lines, Rink and Swan (1979) establish that the PLC of products can be altered. These authors, analysing some 20 empirical PLC studies, conclude that there are different forms of the PLC. Along the same lines, Fu (2009) also argued the existence of a relationship between the success of new product launches and the age of the salespeople and their years of sales experience, an aspect that supports the previous literature suggesting that the sales variable may not be the most appropriate for PLC analysis.

Orbach and Fruchter (2014) developed a model that was able to predict PLC patterns that could not previously be explained. Their study demonstrated that the PLC analysis can and should be intensified. Despite this, the PLC in relation to the development of new products has been investigated only in a very limited way in the scientific literature (Suomala, 2004, p. 198). The evolution of sales and profits is what characterises the PLC; however, there are a wide variety of life cycle forms, which can be due to different causes (Midgley, 1981).

Studies carried out with the objective of identifying the different variables that affect product sales demonstrate that the development of the PLC concept has been based mainly on demand variables, specifically on the theory of innovation diffusion (Bass, 1980; Day, 1981; Lambkin and Day, 1989; Rodríguez Escudero, 2001). These authors showed that the limited predictive capacity of the PLC was due to the use of the sales variable.

There are some works – although they are scarce – such as that of Lambkin and Day (1989), that refer to the use of other variables, based on the analysis of the competitive context and the evolution of competition (supply factors), and that of Aguilar *et al.* (2012), which suggest the importance of companies using other measurement variables. The PLC theory has faced numerous criticisms; however, it continues to be used as an explanatory model of product sales evolution in the academic marketing field. Currently, research in this area has resumed as a consequence of the shortening of the PLC and improvements in information systems.

2.2 Bass model origin and applications

The Bass model was developed primarily to estimate the PLC phases and to predict innovation diffusion in consumer durables (Cetinkaya and Thiele, 2016, p. 264). The model argues that the sales of a new product at a given time are a function of the probability of conversion of the "innovators" and the influence they exert on the "imitators" (Santesmases, 2012, p. 464). First, there is the rapid wave, constituting the innovation rate, due to the spontaneous purchases of potential adopters (innovators). The second phase is the slow wave that spreads through the market triggered by social learning, where the number of adopters increases with the imitation rate (Kaldasch, 2015, p. 6). The adoption of a product takes place at the moment it is introduced into a market. Once the new product is adopted, its diffusion pattern is formed. These two terms can be understood as the breadth and depth of a product in different countries (Palacios, 2013, p. 94). For a correct application of the Bass model, companies must take into account, in the first place, the rapidity with which customers adopt the innovation and, second, whether the enterprise has the appropriate capabilities and sufficient organisational capacity to handle this growth (Ratcliff and Doshi, 2016, p. 272).

In Table II, we list the main authors and their contributions constituting our theoretical framework.

This theoretical framework demonstrates (Moon, 2005, Midgley, 1981, Fu, 2009, Rink and Swan, 1979) that it is not inevitable that companies must adopt different positioning approaches for products and services in each of the PLC stages based on the sales variable. This argument encourages a new line of research based on customers assisted and not on sales.

In this context, this study aims to contribute to the joint research of commercial and marketing managers from theoretical and practical points of view, intensifying PLC analysis and distinguishing between the clients assisted and sales variables, in order to discover which of the two variables is the more useful for studying PLC phases using the Bass model. Thus, we propose the following hypothesis:

H1. The clients assisted variable provides more efficient and more consistent results than does the sales variable for the estimation of the PLC.

3. Methodology

3.1 The econometric model

To carry out this research, the Bass model was developed based on the distribution function $F(t)$, representing adoption in the period t, and its associated density function $f(t)$. From these and following a hazard rate, the probability of being an adopter, for those who are not yet adopters, at time t is: $(f(t))/(1-F(t))$ which is defined in a linear way as:

$$\frac{f(t)}{1-F(t)} = p + q \cdot F(t) \tag{1}$$

where p is the innovation coefficient and q is the imitation coefficient. $p,q \in (0,1)$ must fulfil $p < q$ y $(p+q) < 1$. These parameters are also, respectively, known as external and internal influence coefficients. Thus, the model represents mixed influences (external and internal).

$F(t)$ is the accumulated number of people who adopt in t, $N(t)$ and m measures the ceiling of people who might adopt (maximum number of potential adopters of the product, that is, the potential market): $F(t) = m \cdot N(t)$. Thus, the hazard rate is:

$$\frac{f(t)}{1-F(t)} = p + q \cdot m \cdot N(t) \tag{2}$$

And it can be rewritten based on the accumulated adopters as:

$$\frac{N(t)}{m-N(t)} = p + \frac{q}{m} \cdot N(t) \tag{3}$$

Mahajan *et al.* (1995) explained product acquisition through this modelling, which follows the Bass model.

Research objective	Methodology	Conclusions	Source
Bass model			
Analysis of the product life cycle	Chaos theory	Implications for dynamic product management	Rodríguez-Escudero (1996)
	Bass and mansfield models	Diffusion and adoption of new products in Latin America	Palacios (2013)
	Bass model	The adjustment of the Bass innovation- diffusion model to the data on evolution of sales over time has been satisfactory	Polo (1983)
	Bass model	PLC evolution is normal in homogenous markets	Kaldasch (2015)
	Bass model	Use of the Bass model for the analysis of diffusion of new products	Ratcliff and Doshi (2016)
	Bass model analysis of feature fatigue	Sales evolution data can be used to analyse what features should be integrated to reduce product feature fatigue	Wu *et al.* (2015)
Product life cycle			
Measurement of the product life cycle	Logistic model of demographic growth	Understanding of the inflection points in order to make strategic decisions	Aguilar *et al.* (2012)
Product life cycle	Process management	Proposed project management model	Ferreira *et al.* (2017)
	Mathematical model	Proposed mathematical model	Hachula and Schmeidel (2016)
	Qualitative	Proposed positioning strategies	Moon (2005)
Study of product innovations and their effects on PLC	Literature review	Proposed typologies of different innovations	Miquel and Molla (1982)
Literature review of the product life cycle	Qualitative type inductive-analytical research method	Proposed ESVIPROMER model	Peralta *et al.* (2014)
Review of the modern utility of the product life cycle	Literature review	The PLC provides valuable information for marketing decision making, however the predictive capacity of sales has limitations	Muñiz Ferrer (2008)
Product life cycle studies	Literature review	The identification of 12 distinct types of product life cycle, the classic form being the most common	Rink and Swan (1979)
Analysis of the product life cycle	Chaos theory	Implications for dynamic product management	Rodríguez-Escudero (1996)
	Literature review	Proposed different marketing techniques depending on PLC phase	Suomala (2004)
Predictive model for PLC patterns	Parametric model	The model explains PLC patterns incapable of previous explanation	Orbach and Fruchter (2014)
	Dynamic system model	Improvement in innovation performance in the PLC phases	Zou *et al.* (2016)
Introduction into new markets	Dynamic model	Advantages of access to new markets when the product is in a PLC growth phase	Shankar *et al.* (1999)
Theoretical problems			
New product launches	Growth curve model	The age and experience of vendors can determine the success of new products	Fu (2009)

(*continued*)

Table II.
Summary of the study theoretical framework

Research objective	Methodology	Conclusions	Source
	Extended conceptual design model	Communication improvement (client, user and expert)	Briede-Westermeyer *et al.* (2016)
	Price-time sensitivity model	The advantages of the application of appropriate pricing policies in the PLC phases	Shu *et al.* (2015)
	Bass model	Reduction of the uncertainty of new product launches	Cetinkaya and Thiele (2016)
Conversion rate	Review	Application of scientific methods to sales management to increase prospects and conversion rates	Lendingam (2006)
Applied uses of the Bass model			
Tourism sector	Estimation of tourist demand	New focus on tourist demand estimation methodology based on the dissemination of information by tourists who have previously visited a location	Ayavirina *et al.* (2017)
Automobile sector	Estimation of the diffusion curve in different countries	The effectiveness of a proposed model to estimate the diffusion curve varies depending on country	Zhu *et al.* (2017)
Textile sector	Predicting seasonal fashion demand	Analytical use of the Bass model with the Newsvendor model in the fashion industry. Actual sales data are not available	Spragg (2017)
Communications sector and the digital economy	Introduction of the individual's heterogeneity into Bass model estimations	Differences in Bass model estimations as a function of the age and education of the individuals	Alonso and Arellano (2015)
	New technology diffusion and estimation of new product demand	Determination of the patterns of new technology diffusion	Weissmann (2008)
	New technology diffusion model	The Bass model has adjustment problems when it is applied to the internet sector	López Sánchez *et al.* (2007)

Table II.

From Equation (3) a discrete version of this can be derived, $N(t)-N(t-1)$, this being the number of individuals that adopt at time t, also represented by $S(t)$:

$$S(t) = p \cdot m + (q-p) \cdot N(t) - \frac{q}{m} N(t-1)^2 \tag{4}$$

Regarding the estimation methods, we propose the use of a Minimum Ordinary Least Squares estimate (MOLS) derived from the discrete version of the previous model:

$$N(t)-N(t-1) = \beta_0 + \beta_1 \cdot N(t) + \beta_2 N(t-1)^2 + u(t) \tag{5}$$

where $u(t)$ represents the model error, $N(t-1)$ the accumulated number of individuals who adopt in the previous period $(t-1)$.

In the MOLS estimation, each of the estimated parameters is related to the Bass model items under study. Thus, from the estimation of these and following their relationship with p, q and m:

$$\beta_0 = p \cdot m$$

$$\beta_1 = q - p$$
$$\beta_2 = \frac{-q}{m} \tag{6}$$

However, the MOLS estimation has inconsistencies. Specifically, in addition to the multicollinearity problems detected by Mahajan *et al.* (1995), when the sample size is reduced, the estimations also lack robustness as they do not meet their own definition of the parameters; ($p,q \in (0,1)$ must comply with $p < q$ y $(p+q) < 1$ (Kijek and Kijek, 2010).

To resolve this problem, we used nonlinear estimation methods from the initial equation proposed by the Bass model (1), expressed as a difference equation where: $S(t) = m \cdot (dF(t))/(dt)$, such that:

$$\frac{dF(t)}{dt} = p + (q-p)F(t) - qF(t)^2 \tag{7}$$

The first estimation method used, following Mahajan *et al.* (1995), would be the direct estimation by nonlinear methods of the solution reached by solving the difference Equation (7), whose solution for $f(t)$ would be:

$$f(t) = \frac{\left(\frac{p+q}{p}\right)^2 \cdot e^{-(p+q)t}}{\left[1 + \frac{q}{p} \cdot e^{-(p+q)t}\right]^2} \tag{8}$$

The result of this estimation is obtained by nonlinear methods, in particular by applying a nonlinear estimation by MOLS for the defined equation. The estimation of this function allows us to directly estimate the parameters p, q and m, and from these the estimation of $f(t)$, whose representation allows us to plot the density function previously introduced by the Bass model. We will use in this application of the nonlinear methodology the coefficients estimated by MOLS as a starting point in the iterations.

3.2 Sources of information and data

The data used in this study were provided by Automóviles Citroën España. The two vehicle models analysed are considered to be substitutes, which makes the research more relevant, since variations in the volume of clients assisted and/or the sales of both models cannot be attributed to variations in customer behaviour. This is because both products share a large part of their target customer base:

- C3: utility segment vehicle (3.94-metres long). The client targets are active families with up to two children and couples without children.
- C4 Cactus: compact segment vehicle (4.16-metres long). The client targets are older couples, young couples and single people.

In addition, it must be taken into account that both models represent an important proportion of the manufacturer's sales as follows:

- The C3 has been very well received in the market throughout its life, and continues so to be, with around 4,925 clients being assisted each month. Thus, we can expect the same during the analysed period, in the product maturity phase.
- The C4 Cactus model was launched onto the market August 2014, just as we started collecting data. There were two clear trends in its evolution corresponding to its introduction and growth phases (the first trend showed a marked increase in sales

until August 2015, with a growth rate of 3 per cent) and the maturity of the product in the market (where an average of 4,148 per month clients were assisted in a fluctuating market).

On the other hand, it should be noted that the observations were made at national level and collected by the entire Automóviles Citroën España dealer network, which amounts to 140 dealerships throughout the country. The data were collected over a period of 24 months from August 2014 to July 2016. It so happened that this period coincided with the entry into the market of a new model, the C4 Cactus, while the old model, the C3, continued to be sold.

Two types of variables are considered:

(1) number of clients assisted (prospective clients) by dealership and by the total dealer network as defined by their interest in the C3 and/or C4 Cactus car models of a car dealer network; and

(2) number of sales per dealer and for the total dealer network.

Of the 223,577 clients assisted, 36,819 acquired units of the C3 and C4 Cactus models (sales) at the points of sale during the study period.

This study intensifies the analysis of the PLC, distinguishing between the clients assisted and sales variables, in order to develop a business decision methodology that allows us to differentiate between the uses of both variables. The clients assisted variable is defined as the volume of customers who requested a quote for a car at a dealership. Thus, we counted as clients assisted all the individuals who requested a quote from the dealer, whether or not they purchased a car. However, the sales variable includes only the customers who bought a product.

The aim of this analysis is to show that the utility of the clients assisted variable is superior to the utility of the sales variable for PLC analysis. This is supported by the fact that data on both variables (clients assisted and sales) are easily obtained by the companies. In addition, as has already been stated, the sales variable may be affected by macroeconomic and sociodemographic phenomena related to the economic cycle. But, in addition, it should be noted that the sales variable is more seasonal in the short-term than the clients assisted variable, since vehicle purchases are linked to certain times of the year, specifically the months of March and June. Figure 1 shows how the sales variable demonstrates this effect in 2015 and 2016, while the clients assisted variable does not.

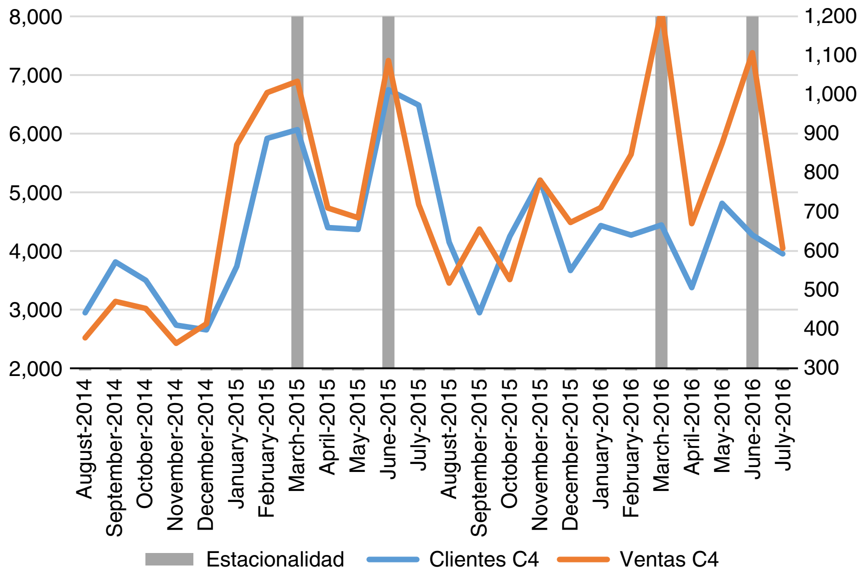
In order to carry out this research, it is necessary to date the stages of the life cycle of these consumer durable products (cars). The study meets this objective by using the above referenced two variables, clients assisted and sales of the vehicle models C3 and C4 Cactus, in order to observe differences in the effectiveness of these variables in the dating methodology. We assess whether the behaviour of the clients assisted and sales variables in the proposed analysis is in accordance with the PLC literature and the Bass model or if, on the contrary, differences are observed in the way these variables allow adjustment of the model.

This research poses an interesting scientific challenge, because the 24-month analysis period allows us to explain the behaviour and timing of each of the phases of the life cycle of a major investment, such as a car, which is located within the automotive sector, an area of great importance to the Spanish economy (Rodriguez *et al.*, 2015, p. 98).

3.3 Analytical strategy

In order to analyse the different behaviours in the different phases of the cycle of both products, the analysis period is divided into the following sub periods, based on the behaviours of the C3 and C4 Cactus models as defined in the previous section:

- August 2014-March 2015: C4 launch period and maturity phase of the C3.



Notes: August, September, October, November, December, January, February, March, April, May, June, July, seasonability, clients, sales

Figure 1. Representation of the seasonality of the sales and clients assisted variables

- April 2015-August 2015: C4 growth period and maturity phase of the C3.
- September 2015-July 2016: both models in their maturity phases.

Using these sub periods, we propose three types of analysis to meet the previously defined objectives:

- Analysis 1: an analysis of the C3 and C4 Cactus models behaviour over the entire period from August 2014 to July 2016 to show if they have different behaviours due to being in different phases of the PLC.
- Analysis 2: an analysis of the behaviour of the C4 Cactus in the periods from August to March 2015, April to August 2015 and September 2015 to July 2016. This analysis aims to verify if the results of the research are consistent with the PLC literature.
- Analysis 3: a comparison of the results for the C3 and C4 Cactus from August 2014 to March 2015 and from April 2015 to August 2015. If the results of this analysis show differences, it would prove that they are in different PLC phases.

4. Results

As previously stated, for each product, the C3 and the C4 Cactus, for the defined study periods, the innovation (p) and imitation (q) coefficients will be estimated through MOLS and NLLS. The results obtained through MOLS for the parameters β_0, β_1 and β_2 do not allow us to obtain consistent estimates of p and q given the restrictions that these parameters must meet (contained in the interval (0, 1), and the sum of both must be less than unity); most estimates do not meet these restrictions. The contrary case is the estimation of parameters p and q, obtained by NLLS, which yield results that meet the aforementioned restrictions. This is why, we present the MOLS results in the appendix, since these values will be necessary as the starting point of the iterations of the nonlinear estimate, but they are not useful to obtain valid results for the p and q estimations.

4.1 Comparison of the behaviour of both models over the entire period (Analysis 1)

Table III shows the estimations of p and q obtained for the two products over the entire analysis period, August 2014 to July 2016, distinguishing between the estimates obtained from the customers assisted and sales variables.

For both variables and both vehicle models, it is observed that the estimations of the innovation coefficient parameter (p) are lower than that of the imitation coefficient (q). On the other hand, the estimations show that the coefficient of innovation of the C4 Cactus is greater than that of the C3, both for the clients assisted variable and for the sales variable. Also, the imitation coefficient (q) is greater, which indicates that the C4 has a higher imitation coefficient both when compared to itself and when compared to the C3. In addition, this result is significant at 1 per cent, although this only occurs for the customers assisted variable (at 10 per cent for the sales variable), which shows a better adjustment (0.96 for the determination coefficient vs 0.92 for the sales variable).

Obtaining a higher imitation coefficient (q) for the C4 Cactus indicates that it is a model in its growth phase, as opposed to the behaviour of the C3.

From this analysis, it can be concluded that the clients assisted variable obtains better adjustment and greater consistency of estimation results in the analysed period. This shows that the clients assisted variable provides more reliable results than the sales variable. From these results, it can be seen that the behaviours of the C3 and C4 models are different throughout the study period and, therefore, it can be inferred that they are in different phases of their PLCs.

4.2 Comparison of the behaviour of the C4 Cactus in the three sub periods (Analysis 2)

Table III gives the estimations of p and q obtained for the C4 Cactus for the sub periods.

In this analysis, it is advisable to highlight, in contrast to the previous analysis (analysis 1 in Section 4.1), that the model does not converge for the sales variable in any of the sub periods analysed. This should be understood as a deficiency of this variable when it comes to presenting Bass model estimations (convergence is reached for random values, therefore there is a lack of consistency in the model adjustment based on this variable), which supports the previous analysis that demonstrated that the sales variable showed a poorer adjustment. This shows that, for the estimation of each of the PLC phases, the clients assisted variable is more efficient and more consistent than the sales variable for the behaviour of the C4 Cactus model. This is a contribution to the previous scientific literature and represents an interesting new line of scientific research (Table IV).

As regard the clients assisted variable, although the results do not give significant estimations, it is observed that the innovation coefficient (p) decreases when we pass from the introduction phase (August 2014-March 2015) to the growth phase (April 2015-August 2015), while the imitation coefficient shows the contrary, increasing from the introduction phase to the growth phase.

	Coef. innovation (p)	Coef. imitation (q)	R^2 of model
Clients assisted			
C4 Cactus	0.0223***	0.0995***	0.963
C3	0.0098	0.0213	0.983
Sales			
C4 Cactus	0.0147**	0.0647*	0.925
C3[a]	0.0001***	0.0086	0.955

Notes: [a]Convergence after reaching a high number of iterations and does not find a value for the intercept of the model (m). The significance of the estimated parameters is given next to each estimation: *5-10 per cent; **1-5 per cent; ***1 per cent

Table III.
NLLS estimation for the complete period August 2014-July 2016

A higher imitation coefficient (q) is obtained in period 2, April 15-August 15, which corroborates the fact that this period should be regarded as a growth phase in the PLC. In addition, the results for both the introduction and growth phases are significantly different for all significance levels (we reject the hypothesis of equality of parameters). However, although the results are open to interpretation, they are not significant for any of the usual statistical significance levels.

As a consequence of these results, there are doubts about whether in choosing the client assisted variable based on the estimations presented, the analytical instrument is given priority over the business objective. In this regard, it is true that beyond the fact that the clients assisted variable correctly fits the Bass model, the authors must take into consideration whether this variable is useful for making successful forecasts or for the future evolution of the product. For this, the researchers made a six-month forward prediction for the C4 Cactus, using both variables (given that the C4 went through different phases of the cycle), employing in both cases a time series moving average model of order 1, this being the model that best represents the behaviour of both variables. The results obtained show that the measurement statistics and goodness of fit of the prediction give similar results with both variables, obtaining a Theil U Index of 0.87 in the case of the clients assisted variable and 0.89 for the sales variable. Although these results and their closeness to 1 show a weak prediction that does not contribute more than the use of criterion $P_{t+1} = X_t$, they show that one variable is not identified as better than the other as a prediction tool. Therefore, as it cannot be otherwise, the authors consider that both variables are equally useful for forecasting.

From everything discussed in this study, it can be stated that the clients assisted variable is more functional and effective than the sales variable due to the following aspects:

- The forecasts obtained from both variables (clients assisted and sales) do not identify one variable as better than the other.
- The ease of registration and control of the clients assisted variable is the same as that for the sales variable.
- However, sales are affected by macroeconomic phenomena that interfere in their usefulness as a reference variable for the analysis of the PLC. This discourages the use of sales as a single evaluation element for a product's economic success.
- In addition, as is noted above, in the short-term, sales are more seasonally variable than clients assisted, since vehicle purchases are linked to certain times of the year, specifically the months of March and June.

In short, the clients assisted variable:

- fits our Bass model better;
- is an equally effective forecasting variable;

	Coef. innovation (p)	Coef. imitation (q)	R^2 of model
Clients assisted			
August 2014-March 2015	0.0287	0.1466	0.954
April 2015-August 2015[a]	0.0014	0.5523	0.975
September 2015-July 2016	No convergence		

Notes: Sales: There is no convergence in any of the sub periods. [a]The convergence value is reached with $\hat{\beta}_0$ = accumulated in the period. The significance of the estimated parameters is given next to each estimate: *5-10 per cent; **1-5 per cent; ***1 per cent

Table IV. NLLS estimation for the C4 Cactus for the three sub periods

And:

- the data for both variables are equally easy for the companies to gather; and
- the clients assisted variable is not affected by macroeconomic phenomena and its seasonality is lower than that of the sales variable.

Based on the above, the authors propose that the clients assisted variable, rather than the sales variable, should be used for PLC analysis.

4.3 Comparison of the behaviour of the C3 for the three sub periods (analysis 3)

Table V shows the previous 3C model analysis. Contrary to what was obtained in the C4 analysis, the results for the different sub periods are all significant at 5 and 1 per cent when both the clients assisted and the sales variables are used. However, if we look at the regression adjustment, again the results obtained for the C3 reinforce those obtained for the C4 Cactus, in relation to the greater efficiency of the clients assisted variable. This analysis shows that, for the estimation of each of the PLC phases, the clients assisted variable is more efficient and more consistent than the sales variable for the behaviour of the C3 model, similar to what was seen in analysis 2 with the C4 Cactus. This supports the results of analysis 2 and shows discrepancies with the previous scientific literature, reinforcing this as an interesting new line of scientific research.

The C3 results again show that the criterion that the innovation coefficient (p) be less than that of the imitation (q) is met. It happens, moreover, that we do not reject the hypothesis that the results of the values of the imitation coefficient are equal, so there is no difference between the two phases.

If we compare these results with those obtained in the C4 Cactus analysis, we see that for the period April 2015-August 2015 the value of q there is significantly higher than that for the C3, which reinforces the evidence that the C4 was in a growth phase, unlike the C3.

5. Conclusion

This work supports the use of the clients assisted variable for PLC analysis, with the purpose of evaluating its usefulness for the Bass model and its utility in the dating of the PLC phases in durable goods as against the repeated use of the sales variable in the existing literature.

This study is in line with the results obtained in previous works, such as those of Rodríguez Escudero (1996); Aguilar *et al.* (2012); Muñiz Ferrer (2008); Mahajan *et al.* (1995), who argue that the sales variable is not the best measure because it is affected by economic and sociodemographic variables. These authors point out the inadequacy of long-term PLC forecasts based on the sales variable given the extreme sensitivity of the sales curve to initial conditions.

	Coef. innovation (p)	Coef. imitation (q)	R^2 of model
Clients assisted C3			
August 2014-March 2015	0.0755***	0.1814**	0.99
April 2015-August 2015	0.0118***	0.1330***	0.99
Sales C3			
August 2014-March 2015	0.0783***	0.2922**	0.97
April 2015-August 2015	0.0113***	0.1232**	0.96

Notes: The significance of the estimated parameters is indicated next to each estimation: *5-10 per cent; **1-5 per cent; ***1 per cent

Table V. NLLS Estimation for the C3 over the three sub periods

The literature reviewed argues that knowledge of the PLC phases has been shown to be an important issue in the business strategy (Shankar *et al.*, 1999, Rink and Swan, 1979, Palacios, 2013). Understanding the PLC allows companies to improve their product-price positioning as well as to improve the effectiveness of their marketing strategies (Kaldasch, 2015; Moon, 2005). In this new business context, there is a broad consensus on the part of the different authors that the PLC should be taken into account when deciding which marketing strategies to follow. As previously explained, the main differences between the authors who, in terms of business practice, defend the usefulness of the PLC and those who criticise it are around the accuracy of the sales variable's predictive capacity for PLC analysis (Muñiz Ferrer, 2008, p. 411).

This statement is in line with previous papers, such as that of Camacho and Galiano (2009), which indicate that sales, which is currently the performance parameter commonly used in PLC analysis, may not be the most consistent variable because it is affected by certain economic phenomena, such as general price increases in the economy (inflation) or by changes in relative prices (some products with respect to others).

In the field of marketing and sales strategies, the analysis and duration of PLC phases is important. The authors compare the use of two variables in PLC dating: sales and clients assisted in the Bass model. This study also establishes the dates and demonstrates the phase or phases in which two specific products are situated within the Spanish automotive sector: the Citroën C3 and C4 Cactus. Both vehicles have been analysed to take into account the acceptance of both models in the study period (Rodríguez *et al.*, 2017, p. 233) and, therefore, the acceptance of the vehicle models cannot be considered as a distorting factor for the study results.

The results obtained, based on a three-step strategic analysis, are as follows:

- Analysis 1 shows that for the complete period August 2014-July 16, the C3 and C4 Cactus models go through different phases. This is also corroborated in the comparative analyses of strategies 2 and 3. This accords with the scientific literature. In this study it has been shown that the clients assisted variable is more efficient for analysis than the sales variable.
- Analysis 2 shows that, for the C4 Cactus, the clients assisted variable provides more efficient and more consistent results for PLC estimation than does the sales variable. These results represent an interesting new line of research, since they allow a greater and better adjustment to the PLC than that obtained by the sales variable.
- Analysis 3 shows that, for the C3, the clients assisted variable gives more efficient and consistent results for PLC estimation than the sales variable. In the previous analysis, it was observed that the C4 Cactus is in its growth phase as it shows a high imitation coefficient, significantly different from the previous period, which does not happen with the C3. These results offer the possibility of improving the effectiveness of marketing strategies throughout the PLC.
- The Bass method estimation obtains results consistent with analyses 1-3 of the study. The conclusion derived is that the clients assisted variable provides, as a result, more efficient and consistent estimations than the sales variable. Therefore, *H1* is accepted.

As a final conclusion, the results show that the C3 and C4 Cactus are in different phases of their PLCs, which is consistent with the previous literature. The C4 Cactus is clearly in a growth phase, where a greater influence of imitators is observed, while the behaviour of the C3 is different and well past that phase.

But the most remarkable thing about this research is that we have shown that the functionality of the clients assisted variable is greater than the sales variable for the Bass model and, therefore, for PLC estimation. These results open a new and interesting research line, which the authors of this study intend to pursue further.

5.1 Business implications

The results of this research are very useful, since they allow marketing decision makers to obtain more consistent estimations of the PLC phases using the Bass model and the clients assisted variable. This is based on the fact that the use of this variable helps to detect if there is any deficiency in the design of the marketing strategy when the client does not make the purchase.

As it has been shown in this study, in the short-term, sales is a more seasonal variable than the clients assisted variable, since vehicle purchases are linked to certain times of the year, the months of March and June. It should be noted that data on both variables are equally easy to obtain. This is due to the fact that the companies keep records of clients assisted so that they know the traffic that has passed through the store and, therefore, to know if their sales volume is due to the number of customers that come to the store or to the conversion rate.

The data on clients assisted are as easily available to companies as sales data. However, the use of this variable improves PLC analysis and this allows an improvement in company forecasting. Thus, making the clients assisted variable a tool to strategically plan investments in innovation and marketing would reduce uncertainty in business management.

We recommend the use of the clients assisted variable in the business field for the estimation of PLC phases. First, it allows us to understand the speed with which customers adopt innovations as well as to determine the behaviour and influence of the innovators on the imitators; and, second, it helps marketing managers to design more efficient communication plans in terms of setting objectives, to decide on the tools to be used, to decide on investment in communications in the different stages of the PLC and/or, to decide to extend the maturity stage, to continue to attract new customers to the dealership and to create brand preference.

5.2 Limitations and future research lines

The main limitation of this research is the absence of previous scientific literature that uses the clients assisted variable in the Bass model. In any case, the theoretical framework of the Bass model in PLC analysis is quite scarce in comparison with other areas of analysis of the product variable (Suomala, 2004, p. 198).

A further limitation of this study is that we focus on an analysis of consumer durables. This limits the extrapolation of our results. Therefore, we recommend replication of this study in other sectors to allow a comparison of results.

It can be considered as a limitation that the time periods analysed do not include the decline and product withdrawal phases, which in the automobile sector are very ephemeral.

On the other hand, the main lines of research lines opened in this study are as follows:

- a PLC analysis that considers all phases;
- analysis of the behaviour of the conversion rate in each of the PLC phases; and
- intensifying the relationship between investment in communication, clients assisted and PLC.

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Appendix

	Constant $\hat{\beta}_0$	Accumulated $N(t)$	Accumulated² $N(t)^2$	Goodness of fit R^2
Clients assisted				
C4 Cactus	3,186.68***	0.0735866**	−6.96082e-07**	0.272285
C3	4,850.1**	−0.000805297	3.96066e-08	0.040949
Sales				
C4 Cactus	542.593***	0.0428166	−1.62690e-06	0.149968
C3	791.984***	−0.00324547	4.90583e-07	0.039722

Notes: The significance of the estimated parameters is indicated next to each estimation. *5-10 per cent; **1-5 percent; ***1 per cent

Table AI. MOLS estimation for the complete period August 14-July16 (analysis 1)

	Constant $\hat{\beta}_0$	Accumulated N (t)	Accumulated² N $(t)^2$	Goodness of fit R^2
Clients assisted				
Launch August 2014-March 2015	4,184.58**	−0.224010	1.26042e-05	0.748000
Growth 2015-August 2015	−29,085.3	1.65602	−1.92912e-05	0.718072
Maturity September 2015-July 2016	10530.1	−0.141597	7.81476e-07	0.248025
Sales				
Launch August 2014-March 2015	789.144*	−0.882860	0.000431456	0.844845
Growth April 2015-August 2015	998.019	0.0225294	−8.64073e-06	0.420443
Maturity September 2015-July 2016	−1,998.80	0.429871	−1.58638e-05	0.323979

Notes: The significance of the estimated parameters is indicated next to each estimation: *5-10 per cent; **1-5 per cent; ***1 per cent

Table AII. MOLS estimation for the C4 Cactus for the different sub periods (analysis 2)

Table AIII.
MOLS estimation for the C4 Cactus for the different sub periods (analysis 3)

	Constant $\hat{\beta}_0$	Accumulated $N(t)$	Accumulated^2 $N(t)^2$	Goodness of fit R^2
Clients assisted				
Launch August 2014-March 2015	5,442.59***	−0.0226429	−2.05370e-07	0.405577
Growth April 2015-August 2015	−8,618.00	0.511121	−4.92505e-06	0.567429
Sales				
Launch August 2014-March 2015	445.238	0.268035	−0.0000381	0.4601
Growth April 2015-August 2015	−128.4121	0.1400623	−4.69e-06	0.2413

Notes: The significance of the estimated parameters is given next to each estimation: *5-10 per cent; **1-5 per cent; ***1 per cent

Corresponding author
Vicente Rodríguez can be contacted at: vicente.rodriguez@unir.net