Modeling innovation diffusion patterns

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Chapter 4

Diffusion of movies in neighboring Mediterranean countries[1]

4.1. Introduction

For firms operating in a global environment, it is useful to understand to what extent adoptions in one country may affect adoptions in another country (Putsis et al., 1997). The knowledge and understanding of the diffusion process of a new product in a specific region or country is obviously of paramount relevance and has clear implications to managers planning to introduce the new product (or another of similar characteristics) in another region or country. Researchers, such as Gatignon, Eliashberg and Robertson (1989), Takada and Jain (1991), Helsen, Jedidi and DeSarbo (1993), Redmond (1994), Kumar, Ganesh and Echambadi (1998) and Putsis et al. (1997) have been interested in these geographical aspects and have examined the differences in the diffusion parameters for durable consumer products among different countries. Differences in the adoption processes are explained by specific factors from each country that are beyond companies' control and that can be grouped into two effects:

- the *country effect*, which considers factors such as geographical consumer mobility, cosmopolitanism, the role of women in the labor force, cultural level, prosperity and life-style, and
- the *time effect*, which considers the time lag between introductions among countries.

A *country effect* means that individual country characteristics influence the diffusion processes of innovations. A *time effect* reveals how the time lag between the introduction of an innovation in the pioneer (or lead) country and subsequent countries (or lag countries) affects the diffusion patterns in the latter countries.

The present study has two objectives. First, we extend basic diffusion models to incorporate distribution, which is a rarely incorporated marketing variable. Then,

[1] This chapter is based on the study of Ruiz and Mas (2001).

we analyze the *country* and *time effects* in the diffusion processes of a number of new products in different European countries. The empirical application is carried out on a group of new movies shown in Spain, France and Italy during the period 1997-1999. In summary, the results show that the Generalized Bass model extended to distribution is, in general terms, revealed as the preferred diffusion model for three countries, Spain, France and Italy. The results also show that there is a *country effect* between Spain and France and between Italy and France, although not between Spain and Italy. However, there is insufficient empirical evidence to show the role played by the *time effect*.

We study the diffusion of new movies. We believe that this is interesting for the following three reasons. First, we extend the application of Bass-type diffusion models to include consumer products other than the commonly studied durables. Second, we study the crucial role that retailers (or exhibitors) play in the diffusion process of movies. The extent to which consumers adopt movies depends on their availability; in other words, on the number of screens showing the movies. Third, although the motion picture industry has received increasing attention from marketing scholars as well as economists in recent years, there has been little emphasis on non-U.S. markets (exceptions are Walls (1997), Neelameghan and Chintagunta (1999) and Elberse and Eliashberg (2003)).

The remainder of this study is organized as follows. We start with a review of relevant literature[2]. We then propose extensions to the Bass model by explicitly incorporating distribution as a decision variable. We then develop the data analysis with movie data from Spain, France and Italy, and examine *country* and *time effects*. Finally, we present the conclusions.

4.2. General background

Although the Bass model has been considered an empirical marketing generalization (Mahajan, Muller and Bass, 1995), it has been criticized for its simplification of reality. Its extensions incorporate different variables in an explicit way, especially those explicitly based on marketing decisions (see Chapter 2, Section 2.4.2.9). The explicit incorporation of marketing variables not only gives the model

[2] Although there is existing literature on forecasting the performance of new movies, (Sawhney and Eliashberg, 1996; Neelameghan and Chintagunta, 1999; Neelameghan and Jain, 1999; Eliashberg, Jonker, Sawhney and Wierenga, 2000) it is not based on Bass-type models, and hence we do not discuss it here

greater realism but also contributes to better business management by considering the possibility of altering the diffusion process through marketing control.

Even though the importance of analyzing distribution as one aspect of the commercialization process has long been recognized (Mahajan, Muller and Bass, 1990, 1993; Mahajan, Muller and Wind, 2000), this marketing variable has received relatively little empirical attention in marketing literature, due mainly to the lack of available data. Furthermore, researchers do not agree on the type of model that should be used to evaluate the impact of distribution on the diffusion process. Jones and Ritz (1991) take the three-stage diffusion process as their starting point. They distinguish between the untapped market, the effective potential market and the current market (Mahajan and Muller, 1979). They consider a system of equations in which two parallel diffusion processes interact, one through retailers (producer to retailers) and the other through consumers (retailers to consumers), since consumers cannot adopt the product if retailers do not offer it. Their system presents the retailers' diffusion process with a modified Bass model (mixed influence diffusion model), and that of consumers with a constant transfer rate (diffusion model of external influence). They link both processes by assuming that each adopter-retailer increases the pool of potential adopter-consumers by a fixed amount. Jones and Ritz (1991) conclude, however, that their model achieves a lower degree of fit than other models that only reflect a single consumer process (producer to consumers) and that do not incorporate marketing variables, such as the Bass model and the NUI model (Easingwood, Mahajan and Muller, 1983).

Mesak (1996) applies a single-equation model (mixed influence diffusion model) that reflects a single consumer diffusion process. His proposal introduces price, advertising and distribution simultaneously, but it does not identify the specific effect of any dimension individually. His results show that the proposed model improves the original Bass model.

Over the last few decades, a fairly large body of research on international diffusion has appeared[3]. Researchers have addressed a number of issues such as the influence of country characteristics -*country effect*- (Gatignon, Eliashberg and Robertson, 1989; Takada and Jain, 1991; Helsen, Jedidi and DeSarbo, 1993; Dekimpe, Parker and Sarvary, 1998), the "waterfall" versus "sprinkler" strategies in the launch of new products across countries (Kalish, Mahajan and Muller, 1995), the time lag between introductions of new products among countries -*time effect*- (Helsen, Jedidi and DeSarbo, 1993; Takada and Jain, 1991; Mahajan and Muller, 1994; Kumar, Ganesh and Echambadi, 1998; Putsis et al., 1997; Elberse and Eliashberg, 2003), the pattern of cross-country interaction -or cross-country effect- (Mahajan and Muller, 1994; Eliashberg and Helsen, 1996; Putsis et al., 1997; Kumar and Krishnan, 2002).

[3] See also Chapter 2, Section 2.4.2.5.

Research on the *country effect* focuses on the influence that different environments (countries or specific geographical areas) have on the diffusion processes of innovations. The rationale behind this issue is that an innovation spreads in different ways among different cultures depending on the socio-cultural and socio-economic environments (Redmond, 1994; Dekimpe, Parker and Sarvary, 1998). Analyzing the introduction of a number of products into different countries, Gatignon, Eliashberg and Robertson (1989), Takada and Jain (1991), Helsen, Jedidi and DeSarbo (1993) and Dekimpe, Parker and Sarvary (1998) show that the differences in diffusion patterns could be attributed to country-specific factors such as geographical consumer mobility, cosmopolitanism, the role of women in the labor force, cultural level, prosperity, life-style, ethnic homogeneity, population growth rates or income/poverty levels.

Research on the *time effect* is concerned with how time lags, which necessarily occur when a new product is launched into different markets in a sequential order, affect the diffusion processes. In other words, when a new product is introduced in a country and some time later it is introduced in other countries, consumers in the lag countries learn about the product from the adopters in the lead country. This learning could lead to different diffusion patterns[4]. Putsis et al. (1997) point out that a sequential release provokes differences in information availability that lead to differences in diffusion patterns across markets. There is, however, no consensus among authors. No clear evidence exists on how the experience of adopters in the lead country affects the adoption decisions of potential adopters in the lag countries. Takada and Jain (1991), Mahajan and Muller (1994), and Kumar, Ganesh and Echambadi (1998), focusing on consumer durables, point out that the longer it takes to introduce an innovation into another country, the quicker the ultimate adoption process will be (a positive relationship between the diffusion parameters and the time lag). However, Helsen, Jedidi and DeSarbo (1993) demonstrate the opposite (a negative relationship). An innovation of a consumer durable that has been introduced in a pioneer country, produces a slowing effect on the diffusion processes in countries where the innovation is later introduced. With regard to the extent of the impact of time lags as opposed to their direction, Elberseand Eliashberg (2003), focusing on experience products, find that the longer the time lag between releases, the weaker the relationship between lead and lag countries. This implies that a movie's release in the following countries should be close to that of the pioneering country, given that this benefits the introduction of the innovation in the lag countries.

In this study we first consider three different diffusion models that all incorporate distribution. After selecting the most appropriate model to describe the diffusion processes of a group of movies in three different countries, we focus on analyzing the existence of *country* and *time effects*. The data covers three countries (Spain, France

[4] Ganesh and Kumar (1996) call this the learning effect.

and Italy), twenty-one movies are shown in Spain and six of these movies are also shown in France and Italy.

4.3. Modeling framework

We divide this section into two parts. In the first part we present and compare different diffusion models that explicitly incorporate the distribution variable, and in the second part we address a cross-national analysis by verifying whether the country specific characteristics and the moment of entrance influence the diffusion processes of innovations.

4.3.1. Diffusion models that include distribution

We calibrate three diffusion models and evaluate the goodness of fit with the correlation between the real and the estimated values of the dependent variables[5] (r), the sum of squared residuals (SSR) and the mean absolute percentage error (MAPE). We consider the Bass model as a naïve model. Two proposals are based on the work of Jain and Rao (1990), another is based on that of Bass, Krishnan and Jain (1994).

As we have seen in Section 2.3.2, the Bass model can be expressed as:

$$f(t) = [\beta_1 + \beta_2 F(t)][1 - F(t)] \tag{4.1}$$

where the random variable t denotes the moment of adoption of a new product by an individual (adopter), β_1 and β_2 are the parameters of innovation and imitation respectively, $f(t)$ is the probability of adoption at time t and $F(t)$ the cumulative distribution function:

$$F(t) = \frac{1 - e^{-(\beta_1+\beta_2)t}}{1 + \frac{\beta_1}{\beta_2} e^{-(\beta_1+\beta_2)t}}. \tag{4.2}$$

We will refer to the Bass model as model 1.

We specify two alternative models (models 2 and 3), which incorporate the distribution variable into the diffusion model. Both models are based on Jain and Rao (1990). The model considers dynamics in the potential number of adopters. If [$F(t)$-$F(t$-1)] is the probability that an (randomly chosen) individual adopts the new product within time interval (t-1, t), and if $\left[F(t) - F(t-1)\right] / \left[1 - F(t-1)\right]$ represents the

[5] We show r instead of R^2 or adjusted-R^2 since the proposed models do not have an intercept term (Judge et al., 1985, pp. 30-31).

conditional probability of an individual adopting within time interval (t-1, t) given that he has not yet adopted it at time t-1, we have:

$$S(t) = [M - N(t-1)]\left[\frac{F(t) - F(t-1)}{1 - F(t-1)}\right] + u(t) \tag{4.3}$$

where $S(t)$ represents sales over time interval (t-1, t), $N(t$-1) the total number of adopters by time t-1, and [M-$N(t$-1)] the potential market at time t.

The size of the potential market is directly influenced by the number of retailers who offer the new product[6]. We incorporate this number in model (4.3) in two ways:

In model 2, we assume that the number of retailers who offer the product (D) affects the potential market (M) in the following way:

(model 2) $$S(t) = \left[M * D(t)^{\delta_1} - N(t-1)\right]\left[\frac{F(t) - F(t-1)}{1 - F(t-1)}\right] + v(t) \tag{4.4}$$

In model 3, we assume that the number of retailers who offer the product affects the effective potential market [M-$N(t$-1)][7]:

(model 3) $$S(t) = \left[M - N(t-1)\right]D(t)^{\delta_2}\left[\frac{F(t) - F(t-1)}{1 - F(t-1)}\right] + w(t) \tag{4.5}$$

where δ_1 and δ_2 are the intermediation parameters, and $v(t)$ and $w(t)$ the error terms, with an average of 0 and variances of σ_v^2 and σ_w^2 respectively.

Finally, model 4 is derived from the Generalized Bass model -GBM- (Bass, Krishnan and Jain, 1994). The GBM is a model that incorporates the marketing variables of price and advertising. It has the following structure:

(model 4) $$\frac{f(t)}{[1 - F(t)]} = \left[\beta_1 + \beta_2 F(t)\right]me(t) \tag{4.6}$$

where $me(t)$ reflects current and lagged marketing efforts. If price and advertising are considered at time t -$P(t)$ and $A(t)$, respectively-, $me(t)$ is a function of the percentages of change of such variables:

$$me(t) = 1 + \lambda_1 \frac{\Delta P(t)}{P(t-1)} + \lambda_2 \frac{\Delta A(t)}{A(t-1)} \tag{4.7}$$

where $\Delta P(t)$ and $\Delta A(t)$ are the changes in price and advertising at time t, respectively, and λ_1 and λ_2 are the diffusion price and advertising parameters,

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[6] See Chapter 2, Section 2.4.2.2, for the authors that have relaxed this restriction and have proposed dynamic potential markets.

[7] The term $D(t)^{\delta_2}$ has been included in Equation (4.5) in a multiplying way so that it will also affect the adoption rate $\frac{F(t) - F(t-1)}{1 - F(t-1)}$ (Jain and Rao, 1990).

respectively; they control the effect of price and advertising, respectively, in accelerating and desaccelerating the diffusion process.

For our particular case, where the marketing variable considered is distribution (in terms of the number of retailers of the new product, *D*), we use:

$$me(t) = 1 + \delta_3 \frac{\Delta D(t)}{[D(t-1)]} \tag{4.8}$$

where parameter δ_3 is the intermediation parameter. Its expected value is positive, since an increase in the number of retailers favors the diffusion process.

The idea behind the proposed models (models 2, 3 and 4) is that the diffusion process of an innovation is governed by the innate innovativeness of consumers and mass media communication, social contagion and also by the number of retailers offering the innovation.

4.3.2. Country and time effects

We now examine the possible differences that may exist in the diffusion parameters of geographically close European countries and the effect that the moment of the innovation's introduction may have on the speed of its adoption in these different countries. The geographical comparisons are made in terms of the parameter of internal influence (parameter of imitation in the Bass model), since (1) the number of imitators of an innovation is generally much greater than the number of innovators, and (2) the imitators are the ones who, through social interaction, influence the diffusion process most (Takada and Jain, 1991; Redmond, 1994).

Previous research (Gatignon, Eliashberg and Robertson, 1989; Takada and Jain, 1991; Helsen, Jedidi and DeSarbo, 1993; Dekimpe, Parker and Sarvary, 1998) on the introduction of innovations into different countries shows that the differences in diffusion patterns could be attributed to country-specific factors such as geographical consumer mobility, cosmopolitanism, the role of women in the labor force, cultural level, prosperity, life-style, ethnic homogeneity, population growth rates or income/poverty levels. Since there are specific country factors that can influence consumer behavior regarding innovations, we test for differences in the diffusion processes of the geographical areas analyzed, i.e. whether there is a *country effect*. Hence, hypothesis 1 is expressed as:

H_1: *The parameter of internal influence, β_2, varies among countries*

We test hypothesis 1 by using an analysis of variance test for all of the countries considered and statistical tests for differences between pairs of countries.

We consider the time lag between the moment an innovation is introduced into the pioneering country (or lead country) and the moment it is introduced into a following country (or a lag country). This time lag can affect the diffusion pattern in the following country. No clear evidence exists on how the experience of adopters in the lead country affects the adoption decisions of potential adopters in the lag countries. Some researchers, such as Takada and Jain (1991), Mahajan and Muller (1994), and Kumar, Ganesh and Echambadi (1998) find that the longer it takes to introduce an innovation into another country, the quicker the ultimate adoption process will be. However others, such Helsen, Jedidi and DeSarbo (1993), find the opposite (see Section 4.2). Accordingly, we test whether time lags affect the diffusion processes in the different geographical areas we are analyzing, i.e. whether there is a *time effect*. Hence, hypothesis 2 is expressed as:

H_2: *The time lag between introductions in two different countries affects the adoption process in the last country in which the product is introduced.*

We test hypothesis 2 with the model proposed by Takada and Jain (1991):

$$y_{ijk} = \alpha_0 + \alpha_1 x_{ijk} + \mu_{ijk} \tag{4.9}$$

where y_{ijk} and x_{ijk} are the differences in the values of the imitation parameters and introduction years for a pair of countries *i* and *j* for product *k*, respectively, α_0 and α_1 are parameters and μ_{ijk} is the error term. We test whether α_1 is significantly different to zero. As in the *country effect*, we test hypothesis 2 across the three countries and between pairs of countries.

4.4. Sample, data and measurement of the variables

Movies are consumer products that can be characterized as entertainment and experience products. It is difficult for consumers to evaluate the quality of movies until after their adoption (Neelameghan and Jain, 1999; Elberse and Eliashberg, 2003). Consumers rely heavily on comments from the people closest to them (family, friends and work-mates) on the movies that are currently being shown, (internal influence), and the promotion that movies receive in the mass media (external influence). Accordingly, movies are appealing products for this research since *a priori* the use of diffusion models of innovations[8] of mixed influence seems appropriate.

Our study focuses on three European Mediterranean countries -Spain, France and Italy-, between September 1997 and March 1999. We examine a total of twenty-one new movies launched in Spain, eight of them also in France, and nine also in Italy (see

[8] Motion picture marketers believe that every motion picture (movie) is unique (Eliashberg et al., 2000), hence each movie has to be considered as a new product

Table 4.1). We only select movies that were exhibited for at least six weeks[9]. The length and form of the product life of the movies differ from one country to another[10].

Table 4.1. Movies analyzed by country.

		SPAIN		FRANCE		ITALY	
Code	Title	Weeks[1]	Launch	Weeks	Launch	Weeks	Launch
1	*The Girl of Your Dreams*	15	15/11/98	-	-	-	-
2	*The Mask of Zorro*	10	29/11/98	7	20/10/98	-	-
3	*P. Tinto's Miracle*	7	20/12/98	-	-	-	-
4	*Mulan*	7	22/11/98	7	01/12/98	-	-
5	*There's Something About Mary*	10	08/11/98	9	17/11/98	8	22/09/98
6	*Saving Private Ryan*	8	20/09/98	8	06/10/98	7	05/11/98
7	*Six Days, Seven Nigths*	8	16/08/98	-	-	-	-
8	*Argameddon*	8	19/07/98	9	11/08/98	-	-
9	*Deep Impact*	7	17/05/98	6	02/06/98	11	21/05/98
10	*The Big Lewoski*	7	17/05/98	-	-	13	07/05/98
11	*Torrente el Brazo Tonto de la Ley*	15	15/03/98	-	-	10	23/07/98
12	*As Good as It Gets*	7	01/03/98	-	-	-	-
13	*The Man in the Iron Mask*	9	12/04/98	6	07/04/98	7	02/04/98
14	*The Full Monty*	19	12/09/97	13	28/10/97	10	19/03/98
15	*Open Your Eyes*	8	21/12/97	-	-	-	-
16	*Seven Years in Tibet*	7	07/12/97	9	02/12/97	-	-
17	*Hercules*	7	23/11/97	-	-	-	-
18	*The Truman Show*	7	01/11/98	-	-	6	12/11/98
19	*Blade*	7	11/09/98	-	-	-	-
20	*The Horse Whisperer*	7	04/09/98	10	08/09/98	6	22/11/98
21	*The Jackal*	7	25/01/98	-	-	-	-

(1): Length of the life cycle of the movie in weeks.
(-): Insufficient information or none available.
SOURCE: *Variety Magazine* (1997, 1998, 1999)

The distribution variable (or the exhibition intensity) is defined as the number of retailers or exhibitors (using the terminology of the motion picture industry) that exhibit the movies examined. We obtain information from *Variety Magazine*, a leading American trade publication of the motion picture industry that provides weekly data on the number of screens where a movie is being exhibited and the box-

[9] Jones and Ritz (1991) discard movies that run for under five weeks.
[10] The life cycle of a typical movie is less than fifteen weeks in the domestic theatrical release (Sawhney and Eliashberg, 1996).

office revenues per screen, according to geographical areas. Finally, the number of spectators has been computed, based on the weekly box-office revenues for each movie, as well as the average price of an entrance ticket, obtained through the Institute of Cinema and Audiovisual Arts (ICAA) in Spain and from the different Embassies.

We focus the study on Spain, France and Italy for several reasons. Firstly, although *Variety Magazine* provides information for ten countries each week, it does not always show the same countries, which means that, for some countries, it is not possible to collect data for a movie exhibited over at least six weeks. Secondly, we are interested in European countries since there is little research on non-US markets. Thirdly, the average price of an entrance ticket was unobtainable for some countries.

4.5. Empirical results

In this section, we first discuss the results we obtain from the model estimation. Next, we test the hypotheses that have been specified in Section 4.3.2 on differences in diffusion patterns among the three Mediterranean countries.

4.5.1. Diffusion model performance

We apply the proposed mixed influence diffusion models to Spanish data. We need non-linear estimation procedures (NLS) (Jain and Rao, 1990) to obtain parameter estimates[11]. For model comparison, we use the fit statistics (MAPE, SSR and r), parameter face validity and the Akaike Information Criterion. However, we have to take into account that since prediction is not the aim of this study, parameter face validity is crucial for evaluating alternative marketing decisions and also to develop the analyses in Section 4.5.2. The parameter estimates and the goodness-of-fit statistics for each movie are shown in Appendix 4A (Table 4A.1).

Examining the estimates, we see that the estimates of external influence, $\hat{\beta}_1$, is significant in 95%, 84%, 42% and 94% of the movies examined by models 1, 2, 3 and 4 respectively, while the estimates of internal influence, $\hat{\beta}_2$, is significant in 66%, 63%, 50% and 73% of the movies analyzed by models 1, 2, 3 and 4 respectively. The estimates of β_1 and β_2 exhibit face validity in terms of their magnitude[12] and direction

[11] Srinivasan and Mason (1986) were the first authors to propose an NLS approach to estimate the parameters in the Bass model.
[12] In their meta-analysis of 213 applications of diffusion models from 15 articles, Sultan, Farley and Lehmann (1990) find that word-of-mouth shows bigger magnitudes than the parameter of external influence.

(see Table 4.2). These results confirm that the consumer adoption process for movies is very sensitive to internal communication (as pointed out by Eliashberg, Jonker, Sawhney and Wierenga (2000)) but also to external communication. In other words, when the Spanish public has to choose one of the movies analyzed in the sample, they are influenced by both sources, the comments of people in their face-to-face group and the promotion of the movies.

The intermediation parameter estimates, $\hat{\delta}_1$, $\hat{\delta}_2$ or $\hat{\delta}_3$, are significant in more than 15%, 50% and 15% of the movies analyzed by models 2, 3 and 4 respectively (see Table 4.2). The significant estimates show the right signs, indicating that the diffusion process of these movies is enhanced by an increase in the number of screens, albeit to a small extent, as the negative signs in models 2 and 3 reveal.

Table 4.2.
Plausibility of estimates - $\hat{\beta}_1$, $\hat{\beta}_2$, $\hat{\delta}_1$, $\hat{\delta}_2$, $\hat{\delta}_3$ - (Spanish data)

	Relative frequencies[1]							
	Model 1		Model 2		Model 3		Model 4	
	Level	%	Level	%	Level	%	Level	%
External influence parameter -β_1-								
Right sign and expected magnitude								
Significant estimates	20/21	95	16/19	84	6/14	43	18/19	95
Non-significant estimates	1/21	5	4/19	21	8/14	57	1/19	5
Wrong sign and non-expected magnitude	0/21	0	0/19	0	0/14	0	0/19	0
Internal influence parameter -β_2-								
Right sign and expected magnitude								
Significant estimates	14/21	67	12/19	63	7/14	50	14/19	74
Non-significant estimates	7/21	33	7/19	37	7/14	50	5/19	26
Wrong sign and non-expected magnitude	0/21	0	0/19	0	0/14	0	0/19	0
Intermediation parameter								
-δ_1-								
Significant estimates			3/19	16				
Non-significant estimates			16/19	84				
-δ_2-								
Significant estimates					7/14	50		
Non-significant estimates					7/14	50		
-δ_3-								
Right sign								
Significant estimates							3/19	16
Non-significant estimates							13/19	68
Wrong sign								
Significant estimates							0/19	0
Non-significant estimates							3/19	16

(1): The number of movies differs among models due to convergence problems.

We analyze the benefit of adding one more parameter to the Bass model. In this respect we follow Bemmaor and Lee (2002). On average, the improvement in MAPE for models 2, 3 and 4 is 17%, 41% and 12% over the corresponding Bass model (see Table 4.3). Therefore, adding the intermediate parameter to the Bass model improves the descriptive accuracy of the model.

Table 4.3.
Benefit of the intermediation parameter (Spanish data)

	Model 1	Model 2	Model 3	Model 4
Avg. MAPE (%)	15,45	12,88	9,15	13,60
Improvement(1) (%)		17	41	12

(1): $\text{Improvement}_i = \left(1 - \frac{\text{Avg. MAPE}_i}{\text{Avg. MAPE}_1}\right) * 100$, $i = 2,3,4$; where sub-index i is referred to model.

The inclusion of the distribution variable in the models allows us to understand how distribution can affect the diffusion process of a movie. This corresponds to the findings of Jones and Ritz (1991) and Neelameghan and Chintagunta (1999). Jones and Ritz (1991) present evidence that retailers' adoption of screens is a key determinant of movie viewership in the United States. Neelameghan and Chintagunta (1999) find that the number of screens on which a movie is released is the most important influence on viewership among the factors that they analyzed (movie attributes such as genre or presence/absence of stars).
The level of significant estimates ($\hat{\beta}_1$, $\hat{\beta}_2$ and $\hat{\delta}_1$, $\hat{\delta}_2$ or $\hat{\delta}_3$, depending on the model) with right signs in model 2, 3 and 4 are at 54%, 48% and 61%, respectively (see Table 4.3). In general terms, model 4 shows better results than models 2 and 3.

Table 4.3.
Plausibility of estimates - $\hat{\beta}_1, \hat{\beta}_2, \hat{\delta}_1, \hat{\delta}_2, \hat{\delta}_3$ - in general terms (Spanish data)

	Relative frequencies(1)					
	Model 2 ($\hat{\beta}_1, \hat{\beta}_2, \hat{\delta}_1$)		Model 3 ($\hat{\beta}_1, \hat{\beta}_2, \hat{\delta}_2$)		Model 4 ($\hat{\beta}_1, \hat{\beta}_2, \hat{\delta}_3$)	
	Level	%	Level	%	Level	%
Significant estimates	31/57	54	20/42	48	35/57	61

(1): The number of movies differs among models due to convergence problems.

Looking at the fitting results (r, SSR and MAPE), Table 4A.1 (see Appendix 4A) shows that the proposed models describe the adoption of movies quite well. The correlation level, r, is higher than 0.90 in more than 83% of the cases (61 out of 73). Identical results are obtained when we examine SSR and MAPE. No model, however, shows a clearly better fit than the others for all the movies examined. However, the Akaike Information Criterion shows that, among models 2, 3 and 4, model 3 is the preferred model in 48% (10 out of 21) of the cases (Table 4.4).

Table 4.4.
Akaike Information Criterion -AIC- (Spanish data)

Movie (code)	Model	AIC	Movie (code)	Model	AIC	Movie (code)	Model	AIC	Movie (code)	Model	AIC
1	Mod.2	23.86	7	Mod.2	24.68	13	Mod.2	24.95	19	Mod.2	25.01
	Mod.3	23.84		*Mod.3*	*23.49*		*Mod.3*	*24.26*		Mod.3	-
	Mod.4	*23.75*		Mod.4	25.43		Mod.4	25.16		Mod.4	-
2	Mod.2	25.02	8	Mod.2	24.84	14	Mod.2	23.94	20	Mod.2	22.34
	Mod.3	25.01		*Mod.3*	*22.29*		*Mod.3*	*23.54*		*Mod.3*	*21.00*
	Mod.4	*24.97*		Mod.4	24.80		Mod.4	23.87		Mod.4	23.14
3	Mod.2	22.24	9	*Mod.2*	*23.86*	15	Mod.2	25.18	21	*Mod.2*	*23.75*
	Mod.3	-		Mod.3	-		*Mod.3*	*21.03*		Mod.3	-
	Mod.4	-		Mod.4	24.42		Mod.4	23.79		Mod.4	24.58
4	Mod.2	25.64	10	Mod.2	-	16	*Mod.2*	*25.44*			
	Mod.3	25.51		*Mod.3*	*19.24*		Mod.3	-			
	Mod.4	*25.50*		Mod.4	21.27		Mod.4	25.52			
5	Mod.2	25.21	11	Mod.2	24.31	17	*Mod.2*	*25.79*			
	Mod.3	*25.16*		*Mod.3*	*24.16*		Mod.3	25.59			
	Mod.4	25.29		Mod.4	24.53		Mod.4	25.73			
6	Mod.2	25.35	12	Mod.2	-	18	*Mod.2*	*23.80*			
	Mod.3	*23.73*		Mod.3	-		Mod.3	-			
	Mod.4	25.60		Mod.4	24.28		Mod.4	24.69			

Cursive indicates the smallest AIC.

In order to compare the results across countries, the four proposed models are applied to the six movies that were shown in all three countries -Spain, France and Italy- (see Appendix 4A, Table 4A.2).

Examining Table 4A.2 (see Appendix 4A) we see that for the French data, the estimate of β_1 is significant in 4, 3, 0 and 4 of the movies examined by models 1, 2, 3 and 4 respectively. The estimate of β_2 is significant in 2, 0, 0 and 3 for models 1 through 4, respectively[13]. For the Italian data, the estimate of β_1 is significant in 6, 6, 1 and 6 for models 1 through 4 while the estimate of β_2 is significant in 6, 4, 2 and 5 for models 1 through 4, respectively[14] (see Table 4.5)

Table 4.5.
Plausibility of estimates - $\hat{\beta}_1$, $\hat{\beta}_2$ - (Spanish, French and Italian data)

	Relative frequencies(1)							
	Model 1		Model 2		Model 3		Model 4	
	Level	%	Level	%	Level	%	Level	%
External influence parameter -β_1-								
Spanish data								
Right sign and expected magnitude								
Significant estimates	6/6	100	6/6	100	2/5	40	6/6	100
Non-significant estimates	0/6	0	0/6	0	3/5	60	0/6	0
French data								
Right sign and expected magnitude								
Significant estimates	4/6	67	3/3	100	0/3	100	4/6	67
Non-significant estimates	2/6	33	0/3	0	3/3	0	2/6	33
Italian data								
Right sign and expected magnitude								
Significant estimates	6/6	100	6/6	100	1/2	50	6/6	100
Non-significant estimates	0/6	0	0/6	0	1/2	50	0/6	0
Internal influence parameter -β_2-								
Spanish data								
Right sign and expected magnitude								
Significant estimates	6/6	100	5/6	83	2/5	40	5/6	83
Non-significant estimates	0/6	0	1/6	17	3/5	60	1/6	17
French data								
Right sign and expected magnitude(2)								
Significant estimates	2/6	33	0/3	100	0/3	100	3/6	50
Non-significant estimates	2/6	33	3/3	0	3/3	0	1/6	17
Italian data								
Right sign and expected magnitude								
Significant estimates	6/6	100	4/6	67	2/2	100	5/6	83
Non-significant estimates	0/6	0	2/6	33	0/2	0	1/6	17

(1): The number of movies differs among models due to convergence problems.
(2): 2 out of 6 estimates for β_2 in model 1 and also 2 in model 4 show wrong signs although these are not significant. These four are the only cases with wrong sign estimates.

[13] For the French data, the estimation approach of models 2 and 3 converges in three out of the six movies.
[14] For the Italian data, the estimation approach of model 3 converges in two out of the six movies.

Hence, in the three European countries, the estimates of β_1 and β_2 exhibit face validity in terms of magnitude and direction, and the level of significance of these estimates exceeds 66% (4 out of 6 movies) in all of the models, except for model 3 and for $\hat{\beta}_2$ for the French data. These results confirm the importance of external and internal communication in the diffusion of this group of movies in the three countries and support the movie industry specialists when they emphasize the importance of intangible factors such as consumer perceptions (external influence) and word-of-mouth (internal influence) to forecast movie success (Neelameghan and Jain, 1999).

Concerning the intermediation parameter -δ_1, δ_2 or δ_3, depending on the model-, the results show that across the three countries (in Spain, France and Italy) the estimates are significant in 2 out of 15, 4 out of 10 and 6 out of 18 of the movies analyzed by models 2, 3 and 4 respectively (see Table 4.6).

Table 4.6.
Plausibility of estimates - $\hat{\delta}_1$, $\hat{\delta}_2$, $\hat{\delta}_3$ - (Spanish, French and Italian data)

	Relative frequencies[1]					
	Model 2		Model 3		Model 4	
Intermediation parameters	Level	%	Level	%	Level	%
- δ_1 -						
Spanish data						
Significant estimates	1/6	17				
Non-significant estimates	5/6	83				
French data						
Significant estimates	0/3	0				
Non-significant estimates	3/3	100				
Italian data						
Significant estimates	1/6	17				
Non-significant estimates	5/6	83				
- δ_2 -						
Spanish data						
Significant estimates			4/5	80		
Non-significant estimates			1/5	20		
French data						
Significant estimates			1/3	33		
Non-significant estimates			2/3	67		
Italian data						
Significant estimates			2/2	100		
Non-significant estimates			0/2	0		
- δ_3 -						
Spanish data						
Right sign						
Significant estimates					1/6	17
Non-significant estimates					4/6	67
Wrong sign						
Significant estimates					0/6	0
Non-significant estimates					1/6	17
French data						
Right sign						
Significant estimates					1/6	17
Non-significant estimates					2/6	33
Wrong sign						
Significant estimates					0/6	0
Non-significant estimates					3/6	50
Italian data						
Right sign						
Significant estimates					4/6	67
Non-significant estimates					2/6	17
Wrong sign						
Significant estimates					0/6	0
Non-significant estimates					0/6	0

(1): The number of movies differs among models due to convergence problems.

Across the three countries, on average, the improvement in MAPE for models 2, 3 and 4 is 32%, 37% and 18% over the corresponding Bass model in the three countries (see Table 4.7). Therefore, adding the intermediate parameter to the Bass model improves the descriptive accuracy of the model. Again, despite the small number of significant estimates of the intermediation parameter, the estimates indicate that the diffusion process of these movies is enhanced by an increase in the number of screens.

Table 4.7.
Benefit of the intermediation parameter (Spanish, French and Italian data)

	Model 1	Model 2	Model 3	Model 4
Spanish data				
Avg. MAPE[(1)] (%)	17,65	11,67	11,35	14,75
Improvement[(2)] (%)		34	36	16
French data				
Avg. MAPE (%)	18,75	7,91	13,22	17,98
Improvement (%)		58	29	4
Italian data				
Avg. MAPE (%)	19,74	16,01	10,98	13,25
Improvement (%)		19	44	33
All countries				
Avg. MAPE (%)	18,71	12,65	11,83	15,33
Improvement (%)		32	37	18

(1): $\text{Avg. MAPE}_i = \dfrac{\sum_{j=1}^{6}\sum_{i=1}^{4}\text{MAPE}_{ij}}{M_i}$, $i = 1,2,3,4$, $j = 1,2,\ldots 6$; where sub-index i is referred to model, j to movie and M_i to the number of movies where the estimation approach converges for model i.

(2): $\text{Improvement}_i = \left(1 - \dfrac{\text{Avg. MAPE}_i}{\text{Avg. MAPE}_1}\right) * 100$, $i = 2,3,4$; where sub-index i is referred to model.

We see that the level of significant estimates ($\hat{\beta}_1$, $\hat{\beta}_2$, $\hat{\delta}_1$, $\hat{\delta}_2$ or $\hat{\delta}_3$, depending on the model) with right signs in model 2, 3 and 4 are at 58%, 40% and 65%, respectively (see Table 4.8). This indicates that, across the three countries, model 4 shows better results (in terms of face validity) than models 2 and 3; as with the Spanish data.

Table 4.8.
Plausibility of estimates - $\hat{\beta}_1, \hat{\beta}_2, \hat{\delta}_1, \hat{\delta}_2, \hat{\delta}_3$ - across the three countries (Spanish, French and Italian data)

	Relative frequencies[(1)]					
	Model 2		Model 3		Model 4	
	$(\hat{\beta}_1, \hat{\beta}_2, \hat{\delta}_1)^{(2)}$		$(\hat{\beta}_1, \hat{\beta}_2, \hat{\delta}_2)^{(2)}$		$(\hat{\beta}_1, \hat{\beta}_2, \hat{\delta}_3)^{(2)}$	
	Level	%	Level	%	Level	%
Spain	12/18	66.67	8/15	53.33	12/18	66.67
France	3/9	33.33	1/9	11.11	8/18	44.44
Italy	11/18	61.11	3/6	50.00	15/18	83.33
All countries	26/45	57.78	12/30	40.00	35/54	64.81

(1): The number of movies differs among models due to convergence problems.
(2): Significant estimates

Looking at the fitting results (r, SSR and MAPE), they indicate that, as with the Spanish data, the proposed models describe the adoption of movies quite well with the French and Italian data (see Appendix 4A, Table 4A.2). The correlation level, r, is higher than 0.90 in more than 88% of the cases (16 out of 18) and in 100% (20 out of 20) of the cases, respectively. Identical results are obtained when we examine SSR and MAPE. Once again, no model, however, shows a clearly better fit than the others for all the movies examined. However, the Akaike Information Criterion shows that, across the three countries, among models 2, 3 and 4, model 4 is the preferred model in 61% of the cases (11 out of 18) (Table 4.9).

Table 4.9.
Akaike Information Criterion -AIC-
(Spanish, French and Italian data)

	Spain		France		Italy	
Movie (code)	Model	AIC	Model	AIC	Model	AIC
5	Mod.2	25.21	Mod.2	-	Mod.2	22.30
	Mod.3	*25.16*	Mod.3	-	Mod.3	22.14
	Mod.4	25.29	Mod.4	24.70	*Mod.4*	*21.15*
6	Mod.2	25.35	*Mod.2*	*23.37*	Mod.2	23.07
	Mod.3	*23.73*	Mod.3	-	Mod.3	-
	Mod.4	25.60	Mod.4	23.48	*Mod.4*	*23.05*
9	*Mod.2*	*23.86*	Mod.2	-	Mod.2	20.95
	Mod.3	-	Mod.3	-	Mod.3	-
	Mod.4	24.42	Mod.4	26.43	*Mod.4*	*20.50*
13	Mod.2	24.95	Mod.2	24.34	Mod.2	25.20
	Mod.3	*24.26*	Mod.3	24.23	Mod.3	-
	Mod.4	25.15	*Mod.4*	*24.08*	*Mod.4*	*24.97*
14	Mod.2	23.94	Mod.2	-	Mod.2	24.13
	Mod.3	*23.54*	Mod.3	23.74	Mod.3	23.72
	Mod.4	23.87	*Mod.4*	*23.54*	*Mod.4*	*23.16*
20	Mod.2	22.34	Mod.2	23.46	Mod.2	22.00
	Mod.3	*21.00*	Mod.3	23.37	Mod.3	-
	Mod.4	23.14	*Mod.4*	*23.23*	*Mod.4*	*19.09*

Cursive indicates the smallest AIC.

The face validity and fitting results for the proposed models show that in general terms models 1, 2, 3 and 4 are adequate in terms of explaining the diffusion process of movies. However, comparing the results for those models that take into account the intermediate parameter, model 4 shows better results. In terms of the number of significant estimates, model 4 shows, across the three countries, the highest percentage and when we combine the indicators of goodness of fit, model 4 gives the greatest r (12 out of 18, 67%) and the smallest SSR (11 out of 18, 61%) and MAPE values (7 out of 18, 39%) in more cases than the other models. Furthermore, the Akaike Information Criterion reveals that among models 2, 3 and 4, model 4 is the preferred model. Hence, the results indicate that model 4 is the most appropriate diffusion model to describe the diffusion process of the selected movies in the three Mediterranean countries, taking distribution into account.

In summary, the results for model 4 in Spain, France and Italy show that the estimates of the parameter of external influence, $\hat{\beta}_1$, are significant for 16 out of 18 movies analyzed (89%), and those of internal influence, $\hat{\beta}_2$, are significant for 13 movies (72%). The estimate the intermediation parameter, $\hat{\delta}_3$, which measures the effectiveness of distribution, is only significant for 6 out of 18 movies (33%). The positive values of $\hat{\beta}_1$, $\hat{\beta}_2$ and $\hat{\delta}_3$ are as expected, since the diffusion process of these movies was enhanced by longer exposure to inter-personal and mass communication, and by an increase in the number of screens. Despite the findings showing the influence of the intermediation parameter on the diffusion processes, we have only enough statistical evidence to state that the parameters of external and internal influence clearly govern the diffusion patterns of the examined movies in the analyzed countries.

4.5.2. Differences among diffusion processes

We analyze whether significant differences exist among the diffusion processes of the six movies shown in Spain, France and Italy. We also study the effect that the time lag in the moment of introduction of the movies regarding the pioneering (lead) country has on the diffusion processes of the following (lag) countries. Given the results obtained in the previous stage, the Generalized Bass model (GBM) extended to distribution -model 4- is used for the cross-national analysis of diffusion processes of movies in the three European countries.

The country effect

Hypothesis 1 -*The parameter of internal influence, β_2, varies among countries*- is tested by using two different tests, a global one to find differences in the diffusion processes for the three countries simultaneously and separate ones for each pair of countries. Given the estimates of the parameter of internal influence, $\hat{\beta}_2$, we are now able to test whether internal influence differs between countries. To this we apply a test that considers all $\hat{\beta}_2$'s simultaneously. The analysis of variance[15] (F-statistic = 13.97, d.f. = (2, 15), prob. = 0.0004) reveals that Hypothesis 1 is confirmed with a confidence level of 99%.

[15] Although we use the estimates of the parameter of internal influence, $\hat{\beta}_2$ (model 4, Table 4.4), the same analysis (F-statistic = 1.02, d.f. = (2, 15), prob. = 0.3850) using the estimates of the parameter of external influence, $\hat{\beta}_1$ (model 4, Table 4.4), reveals similar $\hat{\beta}_1$*'s* among Spain, France and Italy.

There is a *country effect* in the diffusion processes. In other words, the three countries show sufficient differences to yield different consumer behavior patterns and, hence, different diffusion processes for the group of analyzed movies.

We also study whether the differences in the estimates of the parameter of internal influence, $\hat{\beta}_2$, are significant when the countries are examined in pairs. These differences (see Table 4.10) are significant between the pairs of Spain-France and France-Italy, with a confidence level of 95% and 99%, respectively. The differences are not significant, however, in the case of Spain-Italy[16]. Hence, the tests do not detect any important cultural, economic and/or social differences between these two Mediterranean countries that could have caused different preferences for the group of movies analyzed. On the other hand, the geographical closeness of France and her two European neighbors (Spain and Italy) is not sufficient to eliminate the differences in their intrinsic characteristics. The results clearly indicate that a *country effect* does exist between France and Spain, and between France and Italy.

Table 4.10.
Tests for equality of means among countries (t-test).

$\hat{\beta}2(France)$ - $\hat{\beta}2(Spain)$	$\hat{\beta}2(Spain)$ - $\hat{\beta}2(Italy)$	$\hat{\beta}2(France)$ - $\hat{\beta}2(Italy)$
3.56**	0.73	4.86***

***: $p \leq 0.001$; **: $p \leq 0.05$

To the question proposed by Takada and Jain (1991, p.48), "*Are there any cross-national differences in diffusion processes between the home country and the foreign market where the product is to be introduced?*", our results reveal that the geographic, socio-economic, demographic and/or cultural characteristics or other aspects of the Spanish and Italian markets are not different enough to show relevant differences in the diffusion processes of the analyzed group of movies. These characteristics are sufficiently different between these countries and France.

The time effect

In studying the *time effect* it is necessary to observe a sequential release strategy. Table 4.1 reveals that the movies are released in Spain, France and Italy in

[16] We carried out this analysis considering the significant and non-significant estimates of β_2, and we repeat the same analysis by changing the not significant estimates to zeros. The results do not change.

a sequential order[17]. Spain is the pioneering country for three of the six movies (*Saving private Ryan, Deep impact* and *The horse whisperer*) and Italy in the other three (*There's something about Mary, The man in the iron mask* and *The full Monty*). Although there is not a single pioneering country for all the movies, France is revealed as a lag country.

Hypothesis 2 -*The time lag between introductions in two different countries affects the adoption process in the last country in which the product is introduced*- is tested by using the regression model specified in Equation (4.9). The parameter α_1 allows us to verify whether the time lag in the introduction of a new movie either speeds up or slows down the diffusion process in the lag countries.

We estimate α_1 by using Ordinary Least Squares. The results ($\hat{\alpha}_1 = 0.02$, prob. = 0.13), which show that $\hat{\alpha}_1$ is not significantly different from zero[18], indicate that there is insufficient empirical evidence for the hypothesis that a time lag in the introduction of new movies into the examined countries affects the diffusion processes, especially, the imitating behavior of adopters. One possible reason for this result is that as the differences in time between the moments of entrance of the movies in each country is very small, it is not easy to detect any effect on the parameter of internal influence.

Examining Table 4.11 we see the same results as those obtained across the three countries. The *time effect* between pairs of countries is not supported by the data.

Table 4.11.
Time effect between pairs of countries.

	$\hat{\alpha}_1$
(Spain, France)	-0.02
(Spain, Italy)	0.01
(France, Italy)	0.03

None of the estimates is significant

[17] There is one exception since *The man in the iron mask* was released in Spain and France on different days but within the same week.

[18] We carried out this analysis considering the significant and not significant estimates of β_2, and we repeat the same analysis by changing the not significant estimates to zeros. The results do not change. Since, the previous change makes the dependent variable take a value equal to zero sometimes and given that Least Squares applied to a truncated sample can provide biased and inconsistent estimates of the unknown parameters (Judge et al., 1985), we repeat the analysis using Maximum Likelihood instead of Ordinary Least Squares, but the results do not change.

Whereas the *country effect* is one of the reasons for the differences in the diffusion processes of movies in two of the three analyzed countries, the *time effect* does not appear to play a role.

4.6. Conclusions

This research focuses on two of the multiple concerns that managers have regarding the diffusion process of innovations: marketing decision variables and introductions into different markets. Although research on price and advertising is extensive in diffusion modeling, research on distribution is an area that should be addressed more extensively.

Researchers believe that both the socio-economic environment and time lags in introducing the new products into a market are relevant factors in explaining differences among diffusion processes of the same product in different geographical areas. These questions have motivated us to analyze these phenomena in the context of movies, in three Mediterranean European countries, between 1997 and 1999.

Distribution is incorporated into the diffusion models following the proposals of Jain and Rao (1990), who consider price, and those of Bass, Krishnan and Jain (1994), who consider price and advertising. Then we examine whether there are differences among the diffusion patterns of different countries -*country effect*-, as well as how time lags in the introduction of a group of movies into different countries may affect the diffusion processes -*time effect*-.

The empirical application carried out in the three Mediterranean European countries shows that the diffusion process of the analyzed group of movies is appropriately described by the proposed model. However, in the Spanish context the fitting results point out model 3 and the face validity model 4 as the best models. Nevertheless, across the three countries (Spain, France and Italy), results reveal model 4 as the preferred model. Model 4, derived from the Generalized Bass model (GBM) is a flexible model, easy to implement, which nests the Bass model as a special case and incorporates distribution as a marketing decision variable. In model 4, it is obvious that the influence of external sources and the experience of previous adopters are basic factors in reducing the uncertainty of new adopters regarding new movies. The simple knowledge of the existence of an innovation is not enough for an individual to become a new adopter, social communication is a key factor. Accordingly the diffusion processes of the analyzed movies are determined by three factors: two clear factors are the internal knowledge that consumers have about the movies (through advertising, critic reviews or their innate innovativeness) and word-of-mouth interactions (through social contagion among friends, colleagues or other close people who have already seen the movie), another possible factor is the intensity distribution of the movie in the country concerned.

We have detected a *country effect*, i.e. significant differences in consumer preferences between Spain and France and between Italy and France, although not between Spain and Italy. The slight cultural, economic or social differences that might exist between Spain and Italy do not seem to be large enough to provoke any significant difference between the internal influence parameters of their diffusion processes. Despite the idiosyncrasy in Spain and Italy, consumer behavior seems to be more similar than different, and this fact is reflected in the diffusion patterns.

In this sense, the findings of this study reinforce existing knowledge in the area by supporting the theses of Gatignon, Eliashberg and Robertson (1989), Takada and Jain (1991), Helsen, Jedidi and DeSarbo (1993), Redmond (1994) and Kumar, Ganesh and Echambadi (1998), which point out the importance of the own country characteristics in the commercialization of innovations. The knowledge that there are significant similarities between two countries, in our case Spain and Italy, allows managers to design similar marketing plans when they are thinking of commercializing the same innovation in both countries.

Finally, the results do not support the existence of a *time effect* among the analyzed countries. We do not find enough empirical evidence to obtain any conclusions on the hypothesis that time lags in the launch of movies in different countries either accelerate or decelerate the diffusion processes.

Appendix 4A. Summary tables

Table 4A.1.
Parameter estimates for Spain

Movie (code)	Weeks	Model	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{M}$ (10^3)	$\hat{\delta}_1$, $\hat{\delta}_2$ or $\hat{\delta}_3$	r	SSR (10^6)	MAPE
1	15	Mod.1	0.09 ***	0.09	2,854 ***		0.91	11,900	15.77
		Mod.2	0.09 ***	0.09	2,573	0.02	0.91	11,900	16.42
		Mod.3	0.01	0.07	2,829 ***	0.44	0.92	11,700	15.39
		Mod.4	0.09 ***	0.09 *	2,902 **	0.74	0.99	10,600	17.26
2	10	Mod.1	0.13 ***	0.42 ***	4,325 ***		0.99	19,600	8.56
		Mod.2	0.13 ***	0.44 **	4,767 **	-0.02	0.99	19,300	6.37
		Mod.3	0.16 **	0.48 **	4,353 ***	-0.04	0.99	19,200	6.76
		Mod.4	0.13 ***	0.41 ***	4,396 ***	1.35	0.99	18,400	7.44
3	7	Mod.1	0.24 **	0.25	1,082 ***		0.97	2,350	14.80
		Mod.2	0.23 **	0.61 **	8,176	0.61 **	0.99	596	7.91
		Mod.3	Do not converge						
		Mod.4	Do not converge						
4	7	Mod.1	0.10 **	0.30	3,026 **		0.72	18,200	14.17
		Mod.2	0.09	0.29	23,068	-0.36	0.73	17,900	14.83
		Mod.3	0.02	0.25	2,538	0.40	0.77	15,560	12.10
		Mod.4	0.09 **	0.35	2,985 **	-1.23	0.74	15,600	12.75
5	10	Mod.1	0.11 ***	0.24	3,818 ***		0.92	29,000	15.82
		Mod.2	0.09 **	0.15	1,153	0.26	0.93	22,200	10.10
		Mod.3	0.0002	0.11	4,435	1.17	0.94	22,000	10.06
		Mod.4	0.10 ***	0.20 *	4,153 ***	0.84	0.96	25,400	11.06
6	8	Mod.1	0.15 ***	0.51 **	2,632 ***		0.96	22,800	13.11
		Mod.2	0.14 **	0.68 **	9,265	-0.25	0.97	17,600	10.61
		Mod.3	0.07	3.99	2,827 ***	-0.23 ***	0.99	3,480	6.90
		Mod.4	0.15 **	0.50 **	2,656 ***	0.77	0.96	22,600	12.23
7	8	Mod.1	0.17 ***	0.48 **	2,822 ***		0.97	19,400	15.69
		Mod.2	0.16 ***	0.69 **	14,489	-0.32 *	0.99	9,000	11.49
		Mod.3	0.19	2.25	2,989 ***	-0.21 **	0.99	2,750	4.60
		Mod.4	0.17 **	0.48 **	2,844 **	0.98	0.99	19,120	15.80
8	8	Mod.1	0.18 ***	0.45 **	2,583 ***		0.98	12,100	13.08
		Mod.2	0.18 **	0.52 **	5,672	-0.15	0.98	10,600	16.64
		Mod.3	0.25 **	2.06 **	2,715 ***	-0.19 ***	0.99	227	2.30
		Mod.4	0.17 **	0.48 **	2,608 ***	1.53	0.98	10,200	9.85

Table 4A.1.
Parameter estimates for Spain (continued)

Movie (code)	Weeks	Model	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{M}$ (10^3)	$\hat{\delta}_1$, $\hat{\delta}_2$ or $\hat{\delta}_3$	r	SSR (10^6)	MAPE
9	7	Mod.1	0.24 ***	0.40 **	1,905 ***		0.98	5,460	11.74
		Mod.2	0.23 **	0.53 **	4,529	-0.17	0.99	3,010	6.90
		Mod.3	Do not converge						
		Mod.4	0.24 **	0.41 *	1,888 **	-1.12	0.98	5,260	10.68
10	7	Mod.1	0.12 **	0.46 **	562 ***		0.94	265	10.27
		Mod.2	Do not converge						
		Mod.3	0.21 ***	1.45 **	655 ***	-0.29	0.99	30	2.88
		Mod.4	0.11 **	0.43 **	575 ***	0.78	0.97	225	7.30
11	15	Mod.1	0.09 ***	0.26 ***	3,006 ***		0.95	23,100	20.06
		Mod.2	0.09 ***	0.33 ***	9,212	-0.24	0.96	18,700	16.02
		Mod.3	0.20 **	0.72 **	3,149 ***	-0.24 **	0.96	15,900	10.79
		Mod.4	0.09 ***	0.25 ***	3,011 ***	0.30	0.95	23,100	19.67
12	7	Mod.1	0.04	0.13	7,723		0.83	4,670	7.12
		Mod.2	Do not converge						
		Mod.3	Do not converge						
		Mod.4	0.04	0.14	6,968	-0.89	0.84	4,600	7.22
13	9	Mod.1	0.24 ***	0.40 **	2,040 ***		0.97	18,700	26.75
		Mod.2	0.23 **	0.56 **	3,094 **	-0.09	0.98	14,800	18.08
		Mod.3	0.05	5.22	2,080 **	-0.19 **	0.99	18,058	19.62
		Mod.4	0.23 **	0.40	2,065 **	1.21	0.97	7,391	23.26
14	19	Mod.1	0.05 ***	0.25 ***	3,257 ***		0.92	28,300	26.90
		Mod.2	0.04 ***	0.42 ***	5,832 ***	-0.15 ***	0.95	18,100	15.89
		Mod.3	0.06 ***	0.82 ***	3,364 ***	-0.26 ***	0.97	12,200	16.86
		Mod.4	0.03 ***	0.28 ***	3,299 ***	0.88 **	0.95	16,900	21.13
15	8	Mod.1	0.11 **	0.58 **	1,371 ***		0.88	15,500	24.85
		Mod.2	0.09	0.75	4,241	-0.25	0.88	14,800	22.33
		Mod.3	0.03	3.98 **	1,540 ***	-0.28	0.99	233	2.62
		Mod.4	0.07 **	0.52 **	1,435 ***	1.67 *	0.97	3,710	13.30
16	7	Mod.1	0.22 ***	0.49	1,919 ***		0.96	16,900	13.91
		Mod.2	0.21 **	0.71	3,138	-0.11	0.96	14,600	13.78
		Mod.3	Do not converge						
		Mod.4	0.21 **	0.52	1,949 **	0.76	0.96	15,800	14.49

Table 4A.1.
Parameter estimates for Spain (continued)

Movie (code)	Weeks	Model	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{M}$ (10^3)	$\hat{\delta}_1$, $\hat{\delta}_2$ or $\hat{\delta}_3$	r	SSR (10^6)	MAPE
17	7	Mod.1	0.08 **	0.49 *	2,155 ***		0.80	19,700	14.83
		Mod.2	0.12	0.32	497	0.29	0.83	16,600	13.80
		Mod.3	0.03	0.28	2,033 **	0.27	0.83	16,930	13.97
		Mod.4	0.08 *	0.47	2,175 **	0.05	0.80	19,600	14.67
18	7	Mod.1	0.25 **	0.42	1,556 ***		0.97	6,940	16.32
		Mod.2	0.25 **	0.66 **	3,132 **	-0.15	0.99	2,840	12.58
		Mod.3	Do not converge						
		Mod.4	0.25 **	0.43 **	1,557 **	0.13	0.97	6,926	16.61
19	7	Mod.1	0.22 **	0.57 **	1,724 ***		0.97	10,300	15.52
		Mod.2	0.21 **	0.65	2,284	-0.06	0.97	9,510	18.34
		Mod.3	Do not converge						
		Mod.4	Do not converge						
20	7	Mod.1	0.15 **	0.61 **	1,069 ***		0.98	1,510	11.58
		Mod.2	0.13 **	0.78 **	2,442 *	-0.18	0.99	655	8.43
		Mod.3	0.21 **	1.31 **	1,120 ***	-0.15 **	0.99	173	3.29
		Mod.4	0.15 **	0.58 **	1,076 ***	0.21	0.98	1,460	10.11
21	7	Mod.1	0.23 **	0.43 **	1,868 ***		0.98	6,160	13.54
		Mod.2	0.22 **	0.60 **	5,440	-0.22	0.99	2,780	6.28
		Mod.3	Do not converge						
		Mod.4	0.23 **	0.43 **	1,868 **	0.01 **	0.98	6,160	13.54

***: $p \leq 0.001$; **: $p \leq 0.05$; *: $p < 0.1$

Table 4A.2.
Parameter estimates for Spain, France and Italy.

					Spain							France							Italy						
Movie	W_S	W_F	W_I	Model	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{M}$ (10^3)	$\hat{\delta}_1$, $\hat{\delta}_2$ or $\hat{\delta}_3$	r	SSR (10^6)	MAPE	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{M}$ (10^3)	$\hat{\delta}_1$, $\hat{\delta}_2$ or $\hat{\delta}_3$	r	SSR (10^6)	MAPE	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{M}$ (10^3)	$\hat{\delta}_1$, $\hat{\delta}_2$ or $\hat{\delta}_3$	r	SSR (10^6)	MAPE
5	10	9	8	1	0.11^{***}	0.24^{***}	$3,818^{***}$		0.92	29,000	15.82	0.15	-0.13	3,292		0.93	15,047	14.16	0.12^{***}	0.46^{***}	$1,652^{***}$		0.99	1,090	8.46
				2	0.09^{**}	0.14	1,153	0.26	0.94	22,200	10.10	Do not converge							0.18^{***}	0.53^{**}	$1,957^{**}$	-0.04	0.99	831	6.13
				3	0.0002	0.11	4,435	1.17	0.94	22,000	10.06	Do not converge							0.28^{**}	0.83^{**}	$1,676^{***}$	-0.12^{*}	0.99	708	6.89
				4	0.10^{***}	0.20^{*}	$4,153^{***}$	0.84	0.96	25,400	11.06	0.19	-0.11	2,719	-7.25	0.94	11,533	13.10	0.17^{***}	0.44^{***}	$1,679^{***}$	0.34^{**}	0.99	264	5.39
6	8	8	7	1	0.15^{***}	0.51^{**}	$2,632^{***}$		0.96	22,800	13.11	0.27^{***}	0.11^{*}	$3,153^{***}$		0.99	2,910	7.07	0.25^{***}	0.48^{**}	$1,758^{***}$		0.99	2,270	10.64
				2	0.14^{**}	0.67^{**}	9,265	-0.25	0.97	17,600	10.61	0.27^{***}	0.07	2,042	0.08	0.99	2,420	6.01	0.24^{***}	0.63^{**}	$2,363^{**}$	-0.06	0.99	1,370	8.25
				3	0.07	3.98	$2,827^{***}$	-0.23^{***}	0.99	3,480	6.90	Do not converge							Do not converge						
				4	0.15^{**}	0.50^{**}	$2,656^{***}$	0.77	0.96	22,600	12.23	0.28^{***}	0.12^{*}	$3,119^{***}$	-0.49	0.99	2,710	7.25	0.24^{**}	0.43^{**}	$1,805^{***}$	0.58	0.99	1,340	8.56
9	7	6	11	1	0.24^{***}	0.40^{**}	$1,905^{***}$		0.98	5,460	11.74	0.17	-0.05	1,915		0.43	55,540	57.76	0.45^{***}	0.36^{**}	888^{***}		0.99	1,150	56.62
				2	0.23^{**}	0.53^{**}	4,529	-0.17	0.99	3,010	6.90	Do not converge							0.41^{***}	0.70^{***}	$1,007^{***}$	-0.04^{**}	0.99	389	40.45
				3	Do not converge							Do not converge							Do not converge						
				4	0.24^{**}	0.41^{*}	$1,888^{**}$	-1.12	0.98	5,260	10.68	0.24	-0.18	1,528	-3.71	0.80	27,923	53.58	0.42^{***}	0.39^{***}	903^{***}	0.99^{***}	0.99	249	23.16
13	9	6	7	1	0.24^{***}	0.40^{**}	$2,040^{***}$		0.97	18,700	26.75	0.28^{**}	0.42^{**}	$1,756^{***}$		0.99	3,450	9.09	0.16^{**}	0.61^{***}	$1,369^{***}$		0.94	11,700	20.09
				2	0.23^{**}	0.56^{**}	$3,094^{**}$	-0.09	0.98	14,800	18.08	0.28^{**}	0.41	1,633	0.01	0.99	3,440	9.21	0.16^{**}	0.55	1,136	0.04	0.94	11,500	17.46
				3	0.05	5.22	$2,080^{**}$	-0.19^{**}	0.99	18,058	19.62	0.50	0.97	$1,795^{**}$	-0.10	0.99	3,080	11.45	Do not converge						
				4	0.23^{**}	0.40	$2,065^{**}$	1.21	0.97	7,391	23.26	0.28^{**}	0.35	$1,813^{**}$	1.17	0.99	2,640	11.54	0.16^{**}	0.52	$1,504^{**}$	1.52	0.95	9,120	27.86
14	19	13	10	1	0.05^{***}	0.25^{***}	$3,257^{***}$		0.92	28,300	26.90	0.14^{***}	0.12	$2,060^{***}$		0.94	12,100	15.98	0.17^{***}	0.36^{**}	$1,454^{***}$		0.96	8,120	17.68
				2	0.04^{***}	0.43^{***}	$5,832^{***}$	-0.15^{***}	0.95	18,100	15.89	Do not converge							0.17^{***}	0.42^{*}	$1,672^{**}$	-0.04	0.96	7,970	18.70
				3	0.06^{***}	0.82^{***}	$3,364^{***}$	-0.26^{***}	0.97	12,200	16.86	0.36	0.51	$2,106^{***}$	-0.25^{*}	0.95	18,000	15.46	0.01	0.19^{**}	$1,472^{***}$	0.62^{*}	0.98	5,240	15.06
				4	0.03^{***}	0.28^{***}	$3,299^{***}$	0.88^{**}	0.95	16,900	21.13	0.11^{***}	0.12^{**}	$2,113^{***}$	0.99^{**}	0.96	6,870	13.16	0.14^{***}	0.42^{**}	$1,476^{***}$	0.66^{**}	0.99	2,990	13.08
20	7	10	6	1	0.15^{**}	0.61^{**}	$1,069^{***}$		0.98	1,510	11.58	0.19^{***}	0.03	$2,405^{***}$		0.98	4,040	8.45	0.15^{**}	0.49^{**}	743^{***}		0.98	339	4.95
				2	0.13^{**}	0.78^{**}	$2,442^{*}$	-0.18	0.99	655	8.43	0.19^{***}	0.02	2,169	0.02	0.98	4,040	8.52	0.15^{**}	0.46	617	0.05	0.98	331	5.04
				3	0.21^{**}	1.31^{**}	$1,120^{***}$	-0.15^{**}	0.99	173	3.29	0.09	0.01	$2,436^{**}$	0.11	0.98	4,013	12.75	Do not converge						
				4	0.15^{**}	0.58^{**}	$1,076^{***}$	0.21	0.98	1,460	10.11	0.18^{***}	0.01^{*}	$2,494^{***}$	0.57	0.99	3,250	9.25	0.13^{**}	0.42^{**}	803^{***}	0.78^{**}	0.99	18	1.47

W_S: length of the life cycle of the movie in weeks in Spain; W_F: length of the life cycle of the movie in weeks in France; W_I: length of the life cycle of the movie in weeks in Italy;
***: $p \leq 0.001$; **: $p \leq 0.05$; *: $p < 0.1$