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Forecasting the Diffusion of an Innovation Prior to Launch

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1 Problem

Companies that want to grow face a fundamental dilemma: They can only increase their current base of sales substantially if they introduce really new products into the market. However, the risk of a market failure also increases with the degree of innovativeness of the product (Booz, Allen & Hamilton Inc. 1982). Really new products are those which are defined as being not only new to the company but also new to the market (Garcia and Calantone 2002). In this case, the pioneer has to develop the whole market and cannot draw inferences from experiences which another competitor has already made. Hence, the pioneer has to forecast the development of the new category in the market. Of course, future entrants may take away market share from the pioneer. In any case, the first and most important task for a pioneer is to forecast the diffusion of his innovative product category (Thomas 1985).

Forecasting is a topic that Klaus Brockhoff (1977) has been made popular in Germany. However, he has also shown the many pitfalls when being involved in a practical forecasting task. Forecasting the diffusion of a really new product category prior to introduction is in particular very difficult. We can not base our forecast on any past data. In addition, we cannot ask people if and when they would like to adopt the new product. It is highly unlikely that people can imagine what the innovative product can do for them. When cellular phones were first introduced to the market, for example, T-Mobile (Deutsche Telekom AG) thought that its market potential was limited to business users that needed a cellular phone because they did not have much time and had to use such a device while on their business trip. Nowadays, with millions of teenage users they have realized that cellular phones are needed also for people who have a lot of free time and need entertainment. While some techniques for information acceleration (Urban et al. 1997) have been developed, there is general agreement that these techniques do not help much when predicting the diffusion of really new categories because the respondents have no clear idea of how the product may evolve and change their life. The only way is a subjective judgment that is based on analogous products or services (Thomas 1985 and Easingwood 1989). However, this leads to the question what the most analogous product or weighted set of analogous products is. Furthermore, we must decide what kind of information we have to look for to be able to develop a suitable forecast of the diffusion. In more detail, a company is interested in forecasting not only the market potential that can be reached in the very end, but also the diffusion speed which decides both on the break-even time and the profitability of an innovative product.

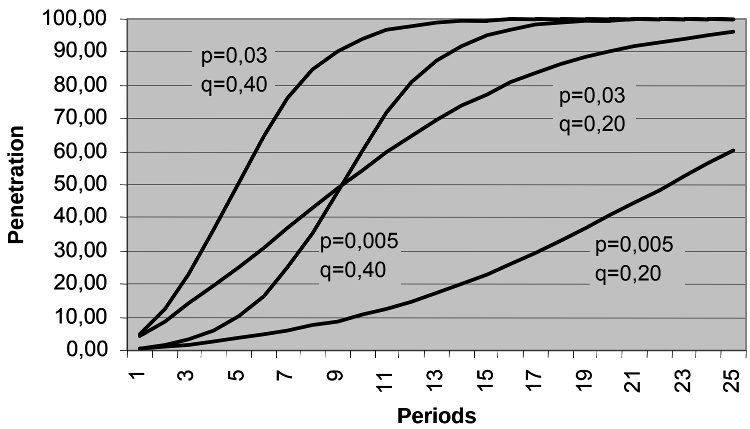
2 Literature review

In the last decades, the Bass model has evolved as the dominant model for explaining and predicting the diffusion of innovations (Bass 1969). It is characterized by an s-shaped penetration of the innovation in the market over a period of time. This shape results from a distinction between innovators and imitators. The first group of people is assumed to adopt an innovative product primarily because of its benefits while the imitators adopt it mostly because of social pressure suggesting that such a product belongs to the usual set of products that a person has to possess (Brockhoff 1999, 121). The Bass model of diffusion can be described mathematically as follows:

$$(1)\quad x_t = \left(p + q \cdot \frac{X_{t-1}}{m}\right)(m - X_{t-1}) \qquad (t = 1,\ldots,T)$$

The resulting development of cumulative sales over time (expressed as penetration of market potential) is depicted in Figure 1.

Figure 1: *Different shapes of the Bass diffusion curve*



The shape of the function depends on the following parameter values:

x_t : Sales units in period t,
p: innovation coefficient,
q: imitation coefficient,
m: market potential,

X_{t-1}: Cumulative sales units up to period t-1.

Knowing these parameter values one can reconstruct a variety of diffusion curves which is depicted in Figure 1 for different values.

This function has been shown to provide a very good fit to many diffusion patterns of innovations observed in the past (Lilien, Rangaswamy, and Van den Bulte 2000). Therefore, we can try to forecast the diffusion of a really new product prior to its introduction by taking the parameter values of a diffusion of an analogous product that is as similar as possible. This can be done in the following different ways:

1. First of all, the user may select a product which he or she feels is the most similar one in terms of diffusion. There are some articles that support this by providing a rather large number of estimates for a variety of products (e.g. Lilien, Rangaswamy, and Van den Bulte 2000, 300-302). In addition, there is also a large number of articles that have already appeared and give information on the parameter values of specific innovations (for an overview, see Mahajan, Muller, and Wind 2000).

2. Because of the high number of already published articles, a person who is searching for the parameter values of the most analogous product has enormous difficulties in finding all the results. As a consequence, meta-analyses have appeared that provide an analysis of the results of published studies. Sultan, Farley, and Lehmann (1990) have condensed the results derived so far. Their main result is:

   (2) $p = 0.03$, $q = 0.38$.

   The meta-analysis also regresses the parameter values p, q, and m on a set of factors that vary over the studies. These may be different product groups or different geographic regions. With this information, we can adjust the overall mean values as given in (2) by product- or region-specific factors. The meta-analysis also accounts for differences in the design of the underlying studies. By adjusting it we can correct possible study biases. Sultan, Farley, and Lehmann (1990) describe in more detail how to proceed in order to get estimates for p and p of analogous products.

3. Another way is not to explain different values of p, q, and m as published in the various articles but to directly derive the parameter values from more than one time series of diffusion data as well as from a larger cross-section of related products. This has been done for the first time in the context of international diffusion (Gatignon, Eliashberg, and Robertson 1989). They have pooled the data for a product across several different countries. While their primary goal was to explain differences in the adoption behavior across countries we may draw inferences from it if we want to introduce the same product in another country. Then we only have to correct country-specific diffusion patterns and can forecast the diffusion of a product in a new country. This has been done in particular in the field of cellular phone services that have been introduced in some countries with a long lag. Many global telecommunication companies like T-Mobile have used similar approaches to forecast the diffusion in the emerging countries in Eastern Europe before enter-

ing the business there. Over time these approaches have become more and more sophisticated. Ihde (1996) has taken the Generalized Bass Model (Bass, Krishnan, and Jain 1994) and estimated the coefficients p, q, and m (relative to the population) of a pooled data base of the diffusion of cellular telephone services in 17 European countries. In addition, he specified a variable market potential depending on the price of the service. All three parameters are specified as functions of variables that may explain differences between the countries. He considered variables like the penetration of information services (telephone, radio, TV, newspapers), the penetration of cars, the urbanization, the amount of air traffic kilometers, and the rate of employed women. His findings are depicted in Table 1:

Table 1: *Diffusion curve parameter values for cellular phone services depending on characteristics of 17 European countries*

Explaining Variables	*Hypothesis*	*Regression Coefficient*	*Significance*
Innovation coefficient p		0.0235	0.00
Imitation coefficient q		0.3047	0.00
Car penetration and urbanization	+	0.3163	0.48
Information services penetration	-	-0.2259	0.39
Competition	+	0.1023	0.09
Rate of employed women	+	1.5583	0.05
Air traffic kilometers	+	-0.0749	0.12
Market potential saturation level m_o		1000	
Scaling parameter b_o		-1.5176	0.00
Price	-	-0.5231	0.00
Exports and Imports	+	0.2357	0.43

Source: Ihde 1996

Later on, this approach was extended to an analysis across 6 different products and 31 different countries (Talukdar, Sudhir, and Ainslie 2002).

4. Pooling data across several entities has also been applied to a different set of products in order to explain differences in the values of the parameter values caused by the presence of certain generic product attributes. Bähr-Sepplfricke (1999) collected data for 20 different consumer durables and telecommunication services. She characterized these products by generic attributes like the product reduces housekeeping time or entertains people or can be bought as a gift. By jointly analyzing these panel data she was able to derive the overall mean parameter values for p, q,

and m as well as their dependence on product attributes. The results are described in Table 2:

Table 2: *Diffusion curve parameter values depending on characteristics of 20 different products*

Explaining Variables of Market Potential	*Coefficient*	*Significance*
Constant Market Potential m	59.1577	0.000
Explaining Variables of Innovation Coefficient	*Coefficient*	*Significance*
Constant Innovation coefficient α_0	0.0097	0.000
Price development	-0.0064	0.000
Continuous Expenses	-0.0029	0.000
Cost Savings	-0.0027	0.000
Time Savings	-0.0029	0.000
Can be bought as gift	-0.0030	0.000
Technical Risk	-0.0030	0.000
Explaining Variables of Imitation Coefficient	*Coefficient*	*Significance*
Constant Imitation coefficient β_0	0.3297	0.000
Price development	0.0637	0.000
Continuous Expenses	0.0811	0.000
Cost Savings	0.0620	0.000
Time Savings	0.0313	0.009
Can be bought as gift	0.0503	0.000
Technical Risk	-0.0208	0.093
Overall Explained Variance	84.86%	

Source: Bähr-Sepplfricke 1999

Now, the idea is to take the innovation which is to be introduced into the market, characterize it by its generic attribute levels, and insert the values into the equation resulting from Table 2 (Bähr-Sepplfricke 1999). Unfortunately, a cross-validation of her analysis did not provide very satisfactory predictions.

5. Instead of searching for the most analogous product, one may combine the forecast of several analogous products. It is a general result that a combination of forecasts outperforms single method forecasts (Meade and Islam 1998). One way may be to select a number of analogous products, to assign weights to the various products and base the forecast on a weighted mean of the parameter values p, q,

and m. A more sophisticated method has been proposed by Bayus (1993) when he attempted to forecast the diffusion of High-Definition Television. First of all, he estimated the parameter values p, q, and m as well as three other parameters characterizing the development of the prices over time. Second, he clustered the products according to these six parameter values. Third, he asked the managers for weights that they would assign to the clusters such that the weighted combination of the clusters would characterize High-Definition TV as best as possible.

These methods rely on sound estimates of p, q, and m. Unfortunately it was established that the parameter values are not independent estimates but depend on the length of the time series and are related to each other (Van den Bulte and Lilien 1997). In particular, they found that with every additional period the m is close to the last value. Only if the time series includes the peak period with the sales maximum then the estimate for m gets stable. But even in this case it is not clear what the ultimate value will be and therefore a validation is often not possible. In addition, Van den Bulte and Lilien (1997) found that p and q depend heavily on the chosen M. On average, an increase of the last observed number of adopters (via more periods of observations) by 10% leads to an increase of m by 5%, a decrease of q by 10%, and an increase of p by 15%. Therefore, it is better to derive information that is independent of each other. If one wants to calculate weighted averages, then it is not clear whether the derived values are still related in a true way to each other. In addition, if one adjusts the parameter values according to the findings of meta-analyses with respect to a product or regional scope then it is also not clear whether the resulting values fit together. In the following, I therefore propose an alternative method that is based on independent information that describes the diffusion of an innovation.

3 Independent descriptors of diffusion processes

As the method of computing weighted averages of p, q, and M for a set of analogous products or the adjustment of these values of meta-analyses lead to values that are no longer related in a proper way to each other, it is necessary to base the inference from analogous products on information that is independent of each other. This should not be done on the basis of parameter values estimated with the help of statistical procedures but on the basis of parameter values that describe the structure of those diffusion curves. Therefore, it is suggested here to take the following descriptors for the analysis:

- Period of peak sales,

- Sales as a percentage of cumulative sales at peak period,
- Sales at peak period.

The period of peak sales has long been recognized as an important descriptor of diffusion processes. The earlier a category or product reaches its peak sales, the earlier the company reaches it break-even point. The peak sales period characterizes the diffusion speed and can be derived by determining the first derivative of the diffusion function (1), setting it to zero and solving it for the period t_{max} (Bass 1969):

$$(3) \quad t_{max} = \ln\left(\frac{q}{p}\right) \Big/ (p+q)$$

Sales as a percentage of cumulative sales at peak period t_{max} describes an important aspect, namely whether the diffusion curve (see Figure 1) represents a steep or flat diffusion. Given a certain level for absolute cumulative sales, the company achieves in the first case very few sales in the very first periods, it is uncertain for a long time whether the product will really take off (Golder and Tellis 1997), and does not reach the break-even point early. The steeper the diffusion is, the more the pioneer must rely on imitators that have to be addressed via mass advertising in an appropriate way. In the case of a rather flat diffusion, the company has higher planning certainty and achieves profitability faster.

With these two descriptors it is possible to fully infer the diffusion speed and the respective diffusion shape of a product. This is plausible because we can rewrite the basic diffusion model by Bass (1) in terms of a normalized market potential of M = 1:

$$(4) \quad f_t = (p + q \cdot F_{t-1})(1 - F_{t-1})$$

f_t : Increase of market potential penetration in period t,

F_t: Market potential penetration in period t.

For estimation purposes, it has been established that it is better to use the formulation in the time domain that means to describe the full diffusion process without knowledge of the previous adoption rate (Srinivasan and Mason 1986):

$$(5) \quad F_t = \frac{1 - e^{-(p+q)\cdot t}}{1 + \left(\frac{q}{p}\right) e^{-(p+q)\cdot t}}$$

Now, the ratio of sales to cumulative sales at peak period is given by:

$$(6) \quad \frac{f_{t\,max}}{F_{t\,max}} = \frac{F_{t\,max} - F_{t\,max-1}}{F_{t\,max}} = 1 - \frac{F_{t\,max-1}}{F_{t\,max}}$$

Note that our two descriptors define two equations (5) and (6) with two unknown parameter values p and q. While it is not possible to derive a closed form solution for p and q, the parameter values can easily be derived with the help of EXCEL's "Solver".

The third descriptor can be used to calculate the market potential because a characteristic of the Bass model is that the adoption process is symmetric, and therefore market potential of adopters is twice as high as adoption in the peak period:

(7) $m = 2 \cdot$ Sales at peak period.

Of course, this information is problematic for inference purposes because the market potential varies according to the nature of the product. However, it is possible to express market potential as a percentage of the maximum addressable potential. In the case of household products this is the number of households in an economy.

Finally, it is emphasized that this procedure only provides valid forecasts until the peak period. Especially, when the diffusion is asymmetric (Easingwood, Mahajan, and Muller 1983), then the sales of all periods after peak will be biased. However, firms are mostly interested in learning something about the early periods: Can they expect an early take-off? Is the diffusion steep or flat and what level of penetration can be achieved until that period? Therefore, as my proposed procedure is not influenced by any asymmetric shape I think that it will provide valuable information.

In the following, I will investigate whether the inference procedure works well in terms of achieving a good R^2 until the peak period. If this is the case, the method is worthwhile. The subsequent section provides the data necessary for deriving the information to infer from analogous products.

4 Predictive Validity of the Inference Method

In order to assess the predictive validity of this approach, I use a data set provided by Lilien, Rangaswamy, and Van den Bulte (2000) to compare my inferred prediction of the diffusion curve with the one resulting from the best fitting parameter values as also given there (note that the results refer to a statistical estimation in the adopter domain while my inference proposal is based on the time-domain). However, I only include those data series that show a curve which is approximately s-shaped.

Table 3: *Predictive Validity of Inferred Compared to Estimated Diffusion Curves*

	Explained Variance up to Peak Inferred	*Explained Variance up to Peak Estimated*	*Explained Variance all Periods Inferred*	*Explained Variance all Periods Estimated*
oxygen steel (USA)	87.55%	61.82%	25.20%	48.85%
oxygen steel (Japan)	85.81%	47.63%	25.20%	55.36%
plastic milk contai. 1 gl.	32.53%	33.08%	27.28%	56.51%
plastic milk cont. 0,5 gl.	71.49%	55.36%	38.51%	49.58%
steam & motor	89.96%	0.80%	29.14%	21.16%
Scanning stores (FRG)	95.53%	48.30%	96.34%	47.35%
Scanning stores (DK)	96.83%	-9.42%	-6.61%	-51.82%
CT scanners (50-99)	91.71%	22.47%	10.22%	10.89%
Ultrasound	88.30%	79.96%	46.71%	70.64%
Mammography	95.62%	93.12%	29.32%	90.93%
hybrid corn	95.02%	87.94%	85.00%	88.56%
artificial insemination	93.32%	70.06%	44.63%	52.74%
bale hay	96.40%	11.33%	79.98%	1.22%
bed cover	2.78%	36.90%	-39.71%	23.68%
Blender	71.87%	63.83%	66.39%	48.14%
can opener	16.96%	26.73%	43.53%	50.79%
electric Coffeemaker	9.38%	43.24%	47.77%	69.80%
coffeemaker ADC	98.58%	-93.07%	19.92%	-12.59%
curling irons	33.81%	-59.24%	-23.30%	38.41%
Dishwasher	83.28%	73.46%	62.95%	65.63%
Disposer	52.12%	-32.95%	18.80%	-27.67%
clothes dryer	10.68%	24.75%	-27.99%	31.73%
hair dryers	66.14%	42.32%	53.10%	9.39%
steam iron	74.61%	45.25%	50.26%	77.49%
microwave	75.42%	70.22%	82.08%	77.05%
Refrigerator	24.13%	12.14%	-64.76%	30.46%
Camcorder	54.93%	-22.74%	41.78%	-32.91%
clothes washer	7.42%	16.03%	9.56%	17.83%
home PC	99.74%	-0.88%	-165.52%	5.93%
telephone answering device	36.45%	42.33%	0.14%	52.12%
television BW	99.12%	3.18%	24.15%	72.93%
TV color	78.85%	12.35%	-155.33%	22.71%
VCR	99.53%	-7.15%	89.03%	1.22%
cordless telephone	71.33%	39.87%	-10.11%	19.13%
cellular telephone	54.93%	40.60%	41.78%	44.65%
Radio	29.03%	-3.52%	14.50%	-28.43%

In my proposal, I just focus on the part until the peak of the sales curve has been reached because diffusion may be asymmetric (Easingwood, Mahajan, and Muller 1983) which is hard to predict prior to launch. In addition, managers are first of all interested to learn about the diffusion until peak sales. In the meantime, they may be able to influence sales in a variety of ways such that sales beyond the growth phase are not an important managerial issue. Therefore, I compare the fit of the curve resulting from my inference proposal with the least squares estimates for the period up to peak sales. This is done on the basis of the explained variance R^2 of the sales data. In a second step, just to get insights into the predictive validity of the whole diffusion curve, I computed the respective R^2 for the complete data series. The results are given in Table 3.

As one can see from the results, the predictions are quite accurate. As actual diffusion curves are very often asymmetric my proposal achieves a better fit up to the peak sales period than the curve fitted with least squares in the adopter domain for the whole data series. Only when we consider the whole curve the prediction is frequently less valid. In any case, this method shows a valid way of forecasting a diffusion curve based on just three descriptors.

5 Meta-Analytic Information

From section 4, we can conclude that the proposal to generate the diffusion curve forecast from three descriptors on analogue products produces valid forecasts. As a consequence, this section provides results on the descriptors for a total of 34 products (data provided by Lilien, Rangaswamy, and Van den Bulte 2000). The results are given in Table 4.

Either the user wants to take a weighted combination of products or one can run a meta-analysis on the basis of a characterization of the products according to their generic attributes like in Bähr-Sepplfricke (1999). Let us apply the first case and forecast the sales of VCR by a weighted combination of products. Of course, the determination of appropriate weights is a highly subjective process but is by far better than guessing the penetration directly. Let us assume that the diffusion of VCRs behaves like a combination of 40% TV Color, 30% Radio, and 30% telephone answering device.

If we take the values for the three analogous products from Table 4, the calculation of weighted averages of the descriptors leads to the following values: Sales peak after 6.7 periods, sales as a percentage of cumulative sales up to peak period = 34.33%, and market potential = 83.37. The determination of a weighted mean of market potential is only possible if this is expressed in terms of penetration of population. Based on these estimates the coefficients p and q can be inferred and are reported in the second row of Table 5. On this basis, we can predict the respective diffusion curve with the help of function (5). The fit as measured by the explained variance is $R^2 = 0.83$ for the periods up to sales peak and $R^2 = 0.8416$ for all periods. If we had taken alternatively the weighted average of the three coefficients p, q, and m directly, we obtain the parameter values reported in the first row.

Table 4: *Inferred Coefficients of Diffusion Curves for different Products*

	Peak Sales period	*Ratio Sales to Cumula-tive at Peak*	*Inferred Market Potential*	*Inferred Innovation Coeff. (p)*	*Inferred Imitation Coeff. (q)*	*Estimated Market Potential*
oxygen steel (USA)	15	22.65%	72.40	0.0005	0.4596	60.5
oxygen steel (Japan)	5	38.24%	61.20	0.0161	0.7521	81.3
plastic milk containers 1 gl	10	23.30%	82.32	0.0044	0.4610	100.0
plastic milk containers ½ gl	23	16.12%	34.24	0.0002	0.3247	28.8
steam & motor	16	23.99%	56.16	0.0002	0.4888	86.7
Scanning stores (FRG)	13	25.94%	19.546	0.0005	0.5292	16702
Scanning stores (DK)	5	50.05%	2.122	0.0047	1.0837	2061
CT scanners (50-99)	7	36.33%	57.80	0.0039	0.7490	57.9
Ultrasound	12	21.88%	122.49	0.0022	0.4378	85.8
Mammography	11	26.09%	88.04	0.0015	0.5293	57.1
hybrid corn	12	38.61%	122.01	0.0000	0.8142	100.0
artificial insemination	7	26.47%	68.00	0.0139	0.4977	73.2
bale hay	10	28.89%	90.00	0.0016	0.5897	92.2
bed cover	19	10.34%	77.40	0.0045	0.1935	72.2
Blender	21	22.78%	51.80	0.0000	0.4637	54.5
can opener	7	17.11%	59.60	0.0384	0.1892	68.0
electric Coffeemaker	11	10.67%	106.80	0.0250	0.1095	100.0
Coffeemak. ADC	4	48.29%	46.80	0.0174	0.9931	32.2
curling irons	4	42.47%	43.80	0.0284	0.8091	29.9
Dishwasher	24	10.47%	59.20	0.0014	0.2059	47.7
Disposer	25	10.97%	63.80	0.0009	0.2175	50.4
clothes dryer	23	9.44%	89.00	0.0026	0.1812	70.1
hair dryers	6	25.36%	56.00	0.0282	0.4230	51.6
steam iron	7	18.23%	72.40	0.0353	0.2361	100.0
microwave	15	20.37%	86.40	0.0009	0.4106	91.6
Refrigerator	17	12.50%	144.00	0.0038	0.2395	99.7
Camcorder	11	30.01%	47.18	0.0007	0.6172	30.5
clothes washer	25	8.53%	133.60	0.0110	0.0330	100.0
home PC (millions of units)	3	60.73%	15.28	0.0235	1.3200	25.8
telephone answering device	7	34.68%	73.48	0.0048	0.7081	69.6
television BW	3	63.26%	52.80	0.0191	1.4173	96.9
TV color	4	42.75%	52.40	0.0278	0.8182	100.0
VCR	7	42.22%	72.00	0.0017	0.8953	76.3
cordless telephone	11	29.94%	62.80	0.0007	0.6154	67.6
cellular telephone	11	30.01%	47.18	0.0007	0.6172	45.1
Radio	10	22.74%	134.55	0.0048	0.4479	100.0

Compared to the method based on descriptors, rather poor fits of R^2 = -14.07% for the periods up to the sales peak and R^2 = 36.18% for the whole time series result. In order to better assess the quality of the proposed method, it is finally compared to the best fitting curve as derived from nonlinear least squares for the periods up to sales peak. The consequences of the poor fit can best be realized by computing the resulting net present values of the three methods up to the sales peak. The proposed method provides a value (14,911) very close to the true value (16,392) while the direct method predicts a net present value that is twice as high as the true value which may lead to completely different managerial conclusions.

Table 5: *Evaluation of the proposed inference of diffusion parameters*

Method	*Innovation Coeff. p*	*Imitation Coeff. q*	*Market Potential m*	*Explained Variance (to Peak Period)*	*Explained Variance (Time Series)*	*Net Present Value*
Weighted Average of Coefficients	0.0140	0.674	90.88	-14.07%	36.18%	32.694
Weighted Average of Descriptors	0.0063	0.695	83.37	83.00%	84.16%	14.911
Nonlinear Least Squares Estimation	0.0016	0.845	83.36	99.83%	82.21%	15.437

6 Summary

Deriving forecasts for innovative durable product categories prior to launch is a very difficult task. Except for product modifications or new bundles of known attributes, we cannot ask the potential user because he cannot imagine the future benefits of such an innovation. Therefore, companies depend on subjective judgment based on analogous products. In principle, this is possible because the diffusion of nearly all innovations follows an s-shaped trend which can be modeled with the help of the Bass model. Very often, there is no direct analogue so that it may be advisable to combine several semi-analogous products to a weighted average. Unfortunately, the coefficients of the Bass model depend on each other and cannot be combined independently.

Instead of using the innovation and imitation coefficient p and q, it is proposed in this paper to describe the diffusion curve by the period in which sales peak and the ratio of sales in the peak period to cumulative sales up to this point of time. It is shown how the parameter values for p and q can be derived from the two descriptors. Based on the additional assumption that penetration in the peak period is 50%, it is also possible to infer the saturation level for cumulative sales. It has been shown that this method reproduces the respective diffusion curves of 34 products very accurately up to the peak period. This finding also implies that predictions should focus on the diffusion up to the peak period because the rest is of minor interest to companies.

In order to help managers with forecasts this article provides the values of the three descriptors for 34 different product categories. Any person who wants to derive analogous products can use this data base and combine the products such that the weighted average of the descriptors of these products is as similar to the category for which the forecast is needed. This is a method that is easy to apply, uses all the experience of the past and shows high face validity.

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