MODELING GENERATIONAL TRANSITIONS FROM AGGREGATE DATA

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Modeling Generational Transitions from Aggregate Data*

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Abstract

Using only aggregate sales data, the model we propose decomposes the diffusion processes of the respective technological generations and tests if different technological generations have different diffusion parameters. It also estimates the location of the generational transition from the old to the new technology. We develop a routine to test whether the maturation point of the old generation occurs before or after the transition to a new technological generation. Finally, we show that, when the aggregate sales data are generated by multiple technological generations, our model does better in forecasting than a single-regime Bass model.

Key words: Technological generations, regime-switching models, diffusion modeling

1 Introduction and motivation

In technology markets, there is nothing as constant as technological change. Broadcasting has changed from Black and White TV over Color TV to Digital TV. Microprocessors have grown from the original Intel 4004, over the Intel 8000 series (8008, 8080, 8088, and 8086) and the Intel 286/386/486 generations to the Intel Pentium generation. In computer consoles, 8-bit systems were replaced first by 16-bit, then by 32-bit and 64-bit and now by 128-bit systems.

Technological change occurs in technology cycles, in which new generations replace old generations (Foster 1986; Norton and Bass 1987). Each such cycle begins with a technological discontinuity or breakthrough (Anderson and Tushman 1991). We also refer to such technological breakthroughs as radical innovations and define them as 'innovations that advance the technological state-of-the-art which characterizes an industry with an order of magnitude and are based on new technologies' (Chandy and Tellis 1998). Technology cycles generally take an S-shape as displayed in Figure 1 (Foster 1986).

The S-curve shows how much performance of a technology - or better, of the products based on that technology - improve over time. In most industries, technologies are characterized by a rather long period of little progress followed by growing success (Foster 1986). After major advances have been made, more incremental and infrequent change sets in, which levels off the performance curve. At the moment an invading technology is introduced, it is often inferior in performance, compared to the established technology. However, if the invading technology has real merit, it typically enters a period of rapid improvement (Utterback 1994). At some point, which we call "generational transition", the invading technology crosses the established technology in performance and the market shifts from the established technology to the invading technology. After some time, this process may be repeated when a new invading technology occurs.

Prior literature, since the work of Fisher and Pry (1971), has addressed the diffusion of successive technological generations, however all based on disaggregate, or generational, sales data. Norton and Bass (1987) was the first paper to model successive generations of technology products on generational sales data, capturing both the diffusion and the substitution pattern. Speece and Maclachlan (1995) were the first to introduce price in a multi-generation diffusion model. The influence of marketing-mix variables over multiple technological generations received further attention from Padmanabhan and Bass (1993) and Danaher, Hardie and Putsis (2001). Mahajan and Muller (1996) developed a model that simultaneously captures the substitution and diffusion pattern and derive guidelines for timing of introduction of new technological generations by monopolists. Islam and Meade (1997) showed that the assumption of constant innovation and imitation coefficients in the Norton and Bass (1987) model is inappropriate and that a model with changing coefficients considerably improves forecasting performance. Bass and Bass (2001) developed a multi-generation diffusion model that separately identifies first-time purchases and repeat purchases.

However, all these prior studies model successive technological generations using sales data on each specific generation. To our knowledge, there is no prior study that offers a methodology to model successive technological generations from aggregate sales data. For example Mahajan and Muller (1996) model the succession of four generations of IBM mainframe computers, using sales data on each of these generations. They do not offer a methodology to model successive generations of IBM mainframes, purely based on aggregate sales data of IBM mainframes. However, often researchers and industry analysts may have no recourse to such disaggregate data. *In this study, we develop a novel modeling approach, which allows for modeling successive technological generations from aggregate sales data over different generations.* Our modeling approach allows capturing underlying technological changes, as soon as they affect a product's market potential. Interestingly, one does not even have to know which, when and how many technological changes have taken place. Of course, in practice data availability impacts the number of possible changes to be included in the model and estimation or interpretation may be cumbersome if one has no external information on specific generations whatsoever (e.g. how many generations underlie the aggregate sales data?). As an example, Figure 2 displays simulated adoption data. We generated these data as the sum of a sequence of the adoption of two technological generations, where these obey the familiar Bass (1969) representation. In fact, the two underlying adoption processes are displayed in Figure 3. The graph of the cumulative adoptions would show two inflection points.

The model we propose considers an aggregate sales series while taking into account the unseen properties of the sales series for each technological generation. Moreover, it allows to extract from the aggregate series an estimate of the first generation series. Such decomposition is relevant for multi-generation diffusion researchers who wish to study the sequence of technological generations and for single-generation diffusion researchers, who wish to test for or purify their data series to only capture a single generation. The model also allows for determining the transition point from the old to the new technology (generational transition). The generational transition point is the time at which the invading or new technology crosses the established or old technology in performance and the market shifts from established to invading technology (operationalization: see model section). Currently, there is no method for identifying this transition point in a multi-generation market. Consequently, one can examine if the transition to the new technology occurs before or after the maturation of the old technology. This is relevant because technology literature implies that the generational transition to the invading technology occurs at the onset of maturation of the established technology (Utterback 1994). It also relates to introduction timing, e.g. do companies delay introduction to fully exploit the established technologies or do they introduce the invading technology long before the maturation of the established technology? We also develop a test that one can use to examine if there are significant differences in market potential between the successive generations. In contrast with prior multi-generation models from generational sales data (Speece and Maclachlan 1995), these differences can also be negative, in that the market potential for the new technology is lower than the market potential of the old technology. In addition, one can test if the innovation (p) and imitation (q) coefficients differ across generations. Finally, we indicate that when one wishes to forecast with aggregate data, our model should outperform a regular Bass model as this model assumes only a single saturation level, while our model allows for multiple saturation levels.

The paper is organized as follows. Section 2 develops our model that can capture multiple generations of adoptions. In essence, this model extends the familiar Bass (1969) model by allowing the parameters to change over time. This change is described by a smooth transition function, hence we label our model a Regime Switching Bass (RSB) model. Indeed, the first regime concerns the first generation, while slowly the second generation comes into play. In the end, there is the sum of two generations. Section 2 also addresses a simple diagnostic test for multiple generations in aggregate adoption data and a method for testing the difference between market potential, innovation and imitation coefficient for the multiple generations. Section 3 applies the model and tests we developed to 2 data series, one for the sales of TV sets, and one for the sales of IBM mainframes (from Mahajan and Muller 1996). Section 4 concludes with implications for further research and some limitations.

2 Model Development

First, we develop our Regime-Switching Bass (RSB) model, which can capture two technological generations. Next, we discuss the case of more than two generations, which is relevant for our illustration on the IBM data. We also discuss a diagnostic test, and the estimation procedure.

2.1 Model Representation

We first develop the model when there are two technological generations. Then we will extend to cases with more than two such generations.

The two generations model

Denote A_t, $t = 1, 2, \dots, T$, as the adoptions in the period running from $t-1$ to t, and denote CA_t as the cumulative number of adoptions up to and including time t. For notational convenience, it is assumed that the analyst has discrete observations. The basic Bass (1969) model then reads as

$$\frac{A_t}{m - CA_{t-1}} = p + \frac{q}{m} CA_{t-1}, \tag{1}$$

where m is the saturation level, p is the coefficient of external influence and q is called the coefficient of internal influence. We can write this model as a discrete differential equation

$$A_t = \alpha_1 + \alpha_2 CA_{t-1} + \alpha_3 CA_{t-1}^2, \tag{2}$$

where $\alpha_1 = pm$, $\alpha_2 = q - p$ and $\alpha_3 = -q/m$. Solving the continuous version of this differential equation shows that CA_t indeed follows an S-shaped pattern.

Suppose the analyst has discrete adoption data, and wonders whether the data can be described by the above Bass model for a single generation, or whether the data are perhaps driven by two generations. The second question would concern which of the parameters p, q, or m is different for the second generation, and whether it would be possible to somehow disentangle the first from the second generation. When a second generation enters the process, with saturation level m_2, then the initial saturation level will rise from, say, m_1 to $m_1 + m_2$, where m_2 measures the saturation level of the second generation of adoptions. Note that the market potential of the new technology thus does not need to be larger than the market potential of the old technology.

The entrance of the second generation may occur immediately or gradually. A function that can describe such a transition, and which is frequently considered in non-linear time series analysis, see for example Franses and van Dijk (2000), is the logistic function. Incorporating this function into the change of saturation levels, one can make m time-varying, that is

$$m_t = m_1 + m_2 \frac{1}{1 + \exp[-\gamma(t - t^*)]}, \tag{3}$$

where the parameter $\gamma > 0$ measures how steep the transition is, and where t^* measures the location of the generational transition. When t equals t^*, only half of the adoption by the second generation has been incorporated in the aggregated adoption series (that is, the saturation level is $m_1 + \frac{1}{2}m_2$), while when t is far in excess of t^*, the new saturation level has become $m_1 + m_2$. When γ is large, this switch from m_1 to $m_1 + m_2$ occurs immediately or at least very rapidly, where m_1 and m_2 are both positive.

The notion of a switching regime can also be considered for the other two parameters in the Bass model, and together this leads to

$$\frac{A_t}{m_t - CA_{t-1}} = p_t + \frac{q_t}{m_t} CA_{t-1}, \tag{4}$$

with additionally

$$p_t = p_1 + p_1^* \frac{1}{1 + \exp[-\gamma(t - t^*)]}, \tag{5}$$

and

$$q_t = q_1 + q_1^* \frac{1}{1 + \exp[-\gamma(t - t^*)]}, \tag{6}$$

where we explain the shift in notation below. Of course, these extensions are relevant in practice only when the quality of the data is sufficiently high. Next, one would be interested to see if the p_1^*, q_1^* and m_2 parameters are equal to zero. It may also be interesting to see how the transition takes place, and how fast the new generation gets incorporated in the total process.

Extensions to k generations

In case there are more than two generations, one needs to modify the two-generation model. Franses and van Dijk (2000) discuss various ways to introduce multiple regimes, but in the present case, it seems most sensible to consider the Bass model with time-varying parameters like

$$m_t = m_1 + \sum_{j=2}^{k} m_j \frac{1}{1+\exp[-\gamma_1(t-t_j^*)]}, \tag{7}$$

$$p_t = p_1 + \sum_{j=1}^{k-1} p_j^* \frac{1}{1+\exp[-\gamma_1(t-t_{j+1}^*)]}, \tag{8}$$

$$q_t = q_1 + \sum_{j=1}^{k-1} q_j \frac{1}{1+\exp[-\gamma_1(t-t_{j+1}^*)]}. \tag{9}$$

If sufficient data are available one can reliably estimate all parameters. However, when there are not enough observations, one might think about only allowing m to vary over time. In addition, if available, one may use external information to further improve estimation and interpretation. For instance, one may know the number of technological generations (k) beforehand, or, one may know m_j, p_j or q_j for one or more generations (e.g. from generational sales data).

2.2 Inference

For simplicity reasons, we discuss inference for the two-generations model. It can easily be extended to k-generations models. One would be tempted to interpret the p_1^*, q_1^* and m_2 parameters in equations (3), (5) and (6) as those corresponding to the second generation. Unfortunately, this only holds for the saturation level m_2. This entails that one can examine if m_1 equals m_2. If p_1^* and q_1^* are found to be equal to zero, then one can confidently say that the two generations have the same internal and external influence parameters, that is, p_1 equals p_2 and q_1 equals q_2. However, if these are not zero, they somehow measure the underlying parameters of the second generation, but in a highly nonlinear way. Hence, also the average of the estimated parameters is not informative.

If one does want to estimate the parameters p_2 and q_2 of the second generation, one needs an estimate of the $CA_{2,t}$ series. One way to obtain this, is by using the estimated parameters $\hat{p}_1^*$, $\hat{q}_1^*$ and $\hat{m}_2$, to construct $\hat{C}A_{1,t}$ using the well-known solution to the differential equation in (??). With this procedure, it is possible to construct $\hat{C}A_{2,t}$, and hence to estimate the relevant parameters for the second generation. Note however that the construction of $\hat{C}A_{1,t}$ disregards the estimation errors for the parameters, and hence that any estimation uncertainty about the first generation series, will be imposed on the estimated second series. This in turn implies that the p_2 and q_2 parameters are estimated with less precision than in case one would have had genuine observations on the second series.

Given the discussion above, it would be interesting to examine if the location t^* of the generational transition differs from the moment that maturity, which we will denote as T^*, occurs for the first generation. Indeed, the model allows us to estimate p_1, q_1, and hence the timing of maturity

$$T^* = \frac{1}{p_1 + q_1} \log \frac{q_1}{p_1}, \tag{10}$$

and it is interesting to see if T^* equals t^*. However, due to this complicated expression for T^*, one cannot write the restriction $T^* = t^*$ such that it leads to restricted values for p_1 and q_1. There is no closed form expression which separates out p_1 from the numerator of the fraction and the fraction in the logarithmic term.

In that case it is better to use the same representation as considered in Franses (2002). Assuming zero values for p_1^* and q_1^*, the model then becomes

$$A_t = \alpha_1 + \alpha_2 CA_{t-1} + \alpha_3 CA_{t-1}^2, \tag{11}$$

with

$$\alpha_1 = \frac{m_t(2m^* - m_t)}{T^*(m_t - m^*)} \log(1 - \frac{2m^*}{m_t}), \tag{12}$$

$$\alpha_2 = \frac{-m^*}{T^*(m_t - m^*)} \log(1 - \frac{2m^*}{m_t}), \tag{13}$$

and

$$\alpha_3 = \frac{1}{2T^*(m_t - m^*)} \log(1 - \frac{2m^*}{m_t}), \tag{14}$$

where m^* denotes the cumulative adoptions at the inflection point.

Finally, it should be stressed that a single generation Bass model for a two generation series must lead to biased forecasts. This is simply due to the fact that the Bass model estimates a fixed saturation level for the total sample, while in reality there are two (or more) such levels. The single-regime model would then yield a weighted average of m_1 and $m_1 + m_2$, where the weights depend on the location of t^* and the size of the two individual saturation levels.

2.3 Testing and estimation

Again for simplicity reasons we discuss the case of two generations, which can easily be extended to k generations. Before one considers estimating the parameters of the highly non-linear regime-switching Bass model, it seems wise first to diagnose if there is any indication of the presence of a second generation of adoptions. Following the literature on switching-regime regression models, it is most common to consider a Taylor expansion of the logistic transition function. For the present case, this means that one can add to the linear regression in (??) the variables t, t^2, t^3, $\ldots$, tCA_{t-1}, t^2CA_{t-1}, t^3CA_{t-1}, $\ldots$ and tCA_{t-1}^2, $t^2CA_{t-1}^2$, $t^3CA_{t-1^2}$, $\ldots$. The number of regressors is in principle infinite, but limited sample sizes may suggest the power of t which is to be considered best. Given the usual sample size of 15 to 30 for diffusion data, it seems perhaps best to consider all regressors up to powers of 2 for t. If the added regressors are significant, based on an F-test, one has evidence of non-linearity. If they are jointly insignificant, one can rely on the one-generation Bass model. A simulation study on the empirical performance of this $F-$test might be insightful.

In case one finds evidence of non-linearity, one should consider estimating the parameters in the switching-regime Bass model. There are many studies in the relevant literature discussing the best estimation strategy. The main conclusion of all these studies is that there is no single best method. One strategy, which is also followed in the empirical section below, is to consider

$$A_t = (p_t + \frac{q_t}{m_t} CA_{t-1})(m_t - CA_{t-1}) + \varepsilon_t, \tag{15}$$

where ε_t is assumed to be a zero mean uncorrelated variable with variance σ^2. This model can be estimated with NLS, which can be performed with any conventional nonlinear optimization procedure. Once one has parameter estimates, one can use individual $t-$tests to see if all parameters are relevant. When comparing the switching-regime Bass model with the single-generation Bass model, one can also rely on the well-known Akaike Information Criterion, for which the smallest value indicates the preferred model. When the aim is to test whether the inflection point of the first generation T^* occurs earlier, later or at the same time as t^*, one should use the model written such that it directly includes an expression for T^*.

Finally, one may want to compare the single-regime and two-regime models in terms of forecasting. When the adoption process is close to full saturation, it is easy to conceive that the forecasts from the two models should become about equal, and hence the last few observations are typically less informative about relative forecast quality. The main differences between the two models would occur around the period just after the transition to the second generation. In that period, the single-regime Bass model will underestimate the final saturation level for a while, as it basically still assumes there is a single generation. The two-regime model acknowledges this second generation and hence would forecast better.

3 Empirical Analysis

This section applies the model and tests developed above to two different markets with successive technological generations. We first discuss the data we use. Then we provide the results of the model and tests.

3.1 Data

For empirical illustration, we use two data sets. The key feature of these data sets is that we have the observations of the various generations, and hence are able to clearly illustrate the merits of our model. The first data set contains data on sales of black and white TV sets and color TV sets, as well as aggregate TV set sales. The second data set contains data on four different generations of IBM mainframe sales and aggregate IBM mainframe sales. We chose these applications for several reasons: (1) unit sales data are available for each generation, so that we can compare our estimations on the aggregate data with the disaggregate sales series for each generation individually; (2) the time frame for which we obtained data on TV set sales contains two technological generations, while that for the IBM mainframe data contains four technological generations; and (3) data were easily available. We obtained data on TV set sales from the Television Factbook. The data on IBM mainframe sales are provided in Mahajan and Muller (1996). We depict the graphs of both the individual generations and aggregate sales patterns for both markets in Figure 4 and 5.

As a courtesy to the reader, we present the TV data in Table 1, whereas the data for the IBM series can be obtained from Mahajan and Muller (1996).

3.2 Results

Model results for TV data

We first discuss the results for the TV data, for which the sample ranges from 1946 to 1978. Suppose we neglect the notion that the data constitute of two regimes, then the single-regime Bass model gives $\hat{m}$ is 673106 (170320), with standard error in parentheses, $\hat{p}$ is 0.0048 (0.0011) and $\hat{q}$ is 0.085 (0.015). When the diagnostic test for the presence of two regimes is applied, where we include t, t^2, tCA_{t-1}, t^2CA_{t-1}, tCA_{t-1}^2, and $t^2CA_{t-1}^2$, the $\chi^2(6)$ test statistic obtains the 1% significant value of 46.441. This indicates that the data indeed contain 2 technological generations. Note that one can only interpret the two regimes as technological generations after examining some external information. For instance, an expansion in distribution capacity or a new adoption segment can all cause similar effects.

The two-regime Bass model, where all three parameters are allowed to switch over time, gives a log likelihood which is only a little larger than that of a two-regime model where only m changes over time. Therefore, we report the results of the latter model. The parameter estimates are: $\hat{p}_1$ is 0.0104 (0.004), $\hat{q}_1$ is 0.070 (0.023), $\hat{m}_1$ is 366328 (134833), and $\hat{m}_2$ is 294549 (129146), while the parameters in the switching function are $\hat{t}^*$ is 19.101 (0.917), which is about 1965, and $\hat{\gamma}$ is 2.113 (4.157), see also Table 2. The maturation of the first generation is estimated to be equal to 23.640, which is about 1970. The AIC of this two-regime model is 18.155, while that of the single-regime model is 18.162. A $\chi^2(1)$ test for the equality of the two saturation levels obtains the insignificant value of 0.206. This means that the eventual size of total adoptions is not different across the two generations.

Finally, our estimation results indicate that the generational transition took place in 1965. It is now interesting to see if this estimate comes close to the maturation of the first generation TV sets. A $\chi^2(1)$ test for the restriction $t^* = 23.640$ gives a value of 24.471, which is significant at the 1% level. Hence, we conclude that the generational transition of black and white TV sets to color TV sets occurred significantly earlier than the time of maturation of black and white TV sets. Table 2 compares our RSB estimates of m_1, p_1 and q_1 with those of the single generation model for black and white TV sets.

Figure 6 displays the estimated switching function and the three data series. Clearly, the switching function matches with the introduction of color TV sets, and hence provides support for the two-generation Bass model.

Model results for IBM data

The annual IBM data span 1955 to 1978, which means that there will be only 23 data points for estimation. Obviously, attempting to estimate all parameters for all generations on this few data points may lead to sever interpretation problems. Therefore, we make some simplifying assumptions. First, we will assume we know from external information, there are four generations. Second, we will restrict p and q to be constant over generations. With four generations and 23 data points, the p and q estimates would not be very meaningful. Therefore, we will also not focus on the location of maturation. Third, we restrict $\gamma_i = \gamma$ for $i = 1, 2, 3$. As above, we consider

$$m_t = m_1 + \sum_{j=2}^{4} m_j \frac{1}{1 + \exp[-\gamma_1(t - t_j^*)]}. \tag{16}$$

Thus we focus solely on the cumulative adoption levels, and the location of the generational transition.

The four-regime Bass model (with fixed steepness parameters, and no changes in p and q), gives that $\hat{m}_1$ is 18645, $\hat{m}_2$ is 119773, $\hat{m}_3$ is 255775 and $\hat{m}_4$ is 213081. A $\chi^2(3)$ test for the equality of these saturation levels is 1.782, which is not significant. It should be stressed though that the number of observations is rather small, and hence the confidence intervals around these estimates are very large, and care must be taken when interpreting these outcomes. The locations of the transition to the new generations get much better estimated, that is, $\hat{t}_1^*$ is 5.988 (0.727), which is about 1961, $\hat{t}_2^*$ is 9.897 (0.538) (around 1965) and $\hat{t}_3^*$ is 13.473 (0.601) (which is around 1968). A $\chi^2(3)$ test that these numbers are equal obtains the highly significant value of 42.876.

Forecasting

To illustrate the forecasting procedure, we consider the two-regime model for the TV data and see if it forecasts better than a single-regime Bass model. We consider the period shortly after the transition to the second generation. Indeed, one might expect the differences between the two models largest in this period, as this crucial feature of the data is overlooked by the single-regime model. The transition time is estimated to be equal to about 19, which would correspond with 1965. As there are some data after this transition needed to enable estimation of this parameter, we compare the single-regime and the two-regime models for the years 1968,1969 and 1970. We estimate the two models for samples which end in the years 1967 to 1969, and each time we generate a one-step ahead forecast. The single-regime model gives the forecasts 11498, 12358 and 13043, and the two-regime model gives 12183, 12920 and 12853. Comparing these with the true observations in Table 1, shows that the mean squared prediction error of the the single-regime model is about three times as large as that of the two-regime model.

4 Conclusion

Marketing scholars have proposed multi-generation diffusion models before. However, all of these models apply generational sales data. In other words, there is no model, which allows for capturing multiple technological generations when one only has access to aggregate (aggregated over different technological generations) sales data. This is an important shortcoming in the literature, since often researchers or industry analysts may not have generational sales data, even more, may not even be aware of multiple generations.

The RSB (Regime-Switching Bass) model we propose in this paper tries to address that shortcoming. Using only sales data that is aggregated across generations, it is able to decompose the diffusion curves of the respective technological generations. Consequently, we can test, from aggregate sales data, if different technological generations have different diffusion parameters (m, p and q in the Bass model). It also allows estimation of the location of the generational transition, or the point at which the buyers migrate from the old technology to the new technology. Since we can also determine the maturation point of the old technology from our model, we have developed a routine to test whether this maturation point of the old generation occurs before or after the transition from the old to the new technological generation. Finally, we show that, when the aggregate sales data are generated by multiple technological generations, the model we develop does better in forecasting than a single-regime Bass model.

Further Research

This model is of great interest to diffusion researchers. First, when one obtains sales data of a product, one does not always know if there are multiple generations that underlie the data. For instance, if one obtains CD player sales, then often these also include regular stand-alone CD players, car CD players, and CD-Walkmans. These are all different generations of the product that were commercialized in different time periods, each with a different market potential and possibly different diffusion parameters. Forcing these parameters to be one and the same in a single generation Bass model is a serious misspecification, which may lead to erroneous conclusions. Our model allows one to test if data are generated by a single or multiple generations and thus can make researchers aware of possible misspecification.

Second, the RSB model we propose can be used to extract diffusion parameters of different generations from aggregate sales data. It can also be used to determine the time of generational transition and old generation maturation. In this manner, it relates to ongoing literature streams on introduction timing of new technological generations (Mahajan and Muller 1996) and the diffusion parameters of multiple generations (Islam and Meade 1997; Norton and Bass 1987).

Third, the RSB model may optimize forecasting, especially around the location of the generational transition. This is of great practical value to market research professionals.

Fourth, the RSB model may also be usefully extended to other applications. One possible application that comes to mind is re-launches of movies. Often, a movie is released multiple times. For instance, most blockbuster movies (e.g. Gladiator), which are introduced much before Oscar night, are introduced to the theaters a second time just before Oscar night to enhance chances of winning an Oscar. The model can capture the sales pattern this re-launch generates.

Limitations

As any model, also the RSB model we propose suffers from a number of limitations, which we hope future research may address. First, the estimate for the market potential of the first generation is independent of the introduction of the second generation. One might want to allow the diffusion pattern of the first generation to change once a new generation is introduced. However, this implies that at the same time two changes are incorporated in the aggregate sales series. Only with specific additional assumptions, the characteristics of these two changes can be identified.

Second, we did not incorporate marketing mix instruments in the model. Although this is a shortcoming to the current version of the model, there is no a priori reason - except for data availability - why marketing mix instruments cannot be incorporated in this model. Extensions of the model in this direction would be in line with earlier extensions of the Bass model that include marketing variables.

Third, the model does not decompose sales in new adoptions and repeat purchases. Fourth, the model identifies diffusion processes underlying the aggregate sales curve. Without further external information, there may be several other phenomena - besides different technological generations - such as extensions in distribution capacity or different adoption categories, which may explain the increase in market potential. Therefore, whenever researchers find evidence of non-linearity in a sales series, they should explore possible other causal factors, in addition to transition between technological generations. Nonetheless, we find that in our illustrations, the estimated technological generations map extraordinarily well on the individual observed generations.

Although these are all valid points of criticism, we believe that this model enriches the literature on multi-generation diffusion models. We cannot but hope that future research addresses some of its limitations.

Table 1: Annual sales of TV sets the USA, in 1000s (source: Television Factbook)

Year	BWTV	CTV	Total
1946	6		6
1947	179		179
1948	970		970
1949	2970		2970
1950	7355		7355
1951	5312		5312
1952	6194		6194
1953	6870		6870
1954	7405	5	7410
1955	7738	20	7758
1956	7351	100	7451
1957	6388	85	6473
1958	5051	80	5131
1959	6278	90	6368
1960	5709	120	5829
1961	6168	147	6315
1962	6696	438	7134
1963	7236	747	7983
1964	8360	1404	9764
1965	8753	2694	11447
1966	7702	5012	12714
1967	6001	5563	11564
1968	6996	6215	13211
1969	7117	6191	13308
1970	6900	5320	12220
1971	7647	7274	14921
1972	8239	8845	17084
1973	7297	10071	17368
1974	6868	8411	15279
1975	4418	6219	10637
1976	5937	8194	14131
1977	6090	9341	15431
1978	6733	10674	17407

Table 2: Estimation results for the first generation of TV data

Parameter	RSB on aggregate data	Bass on generational data
m_1	366328	295253
p_1	0.0104	0.0136
q_1	0.070	0.071

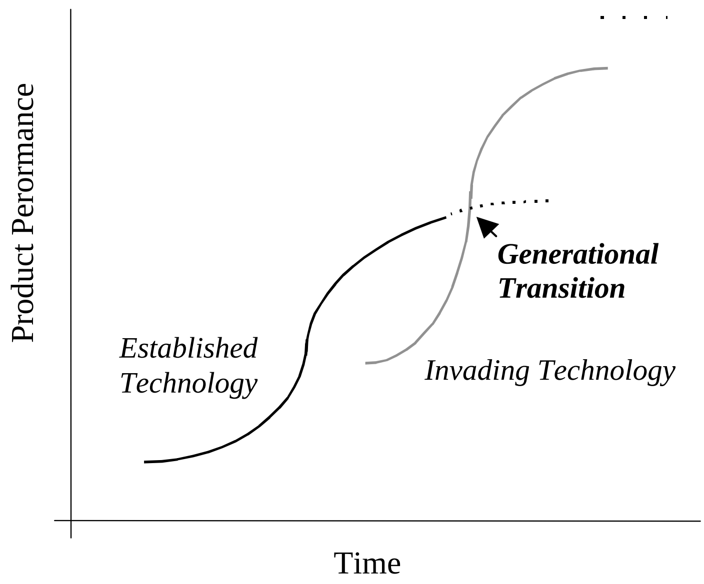

Figure 1: Two technological generations, adapted from Foster (1986) and Utterback (1994)

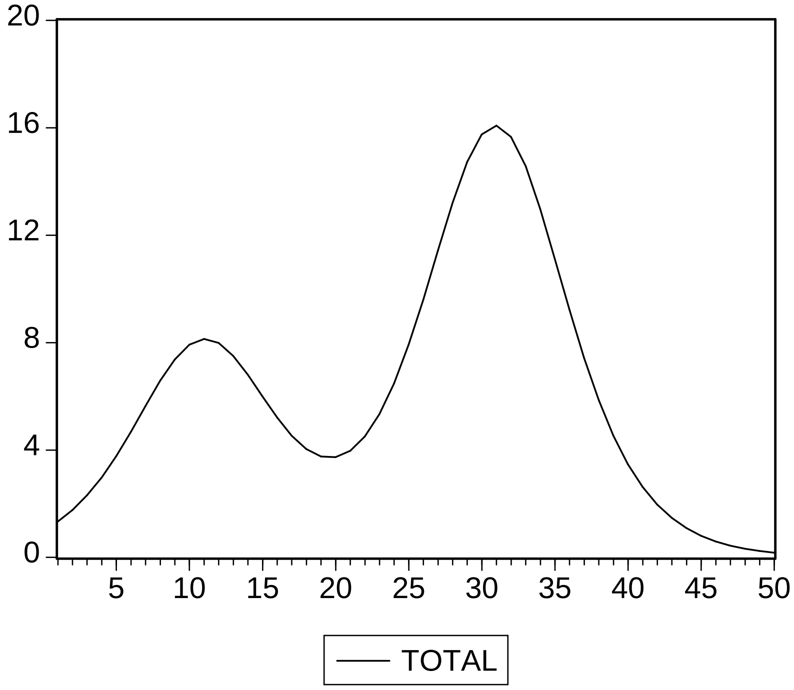

Figure 2: Exemplary shape of new adoptions when there are two inflection points

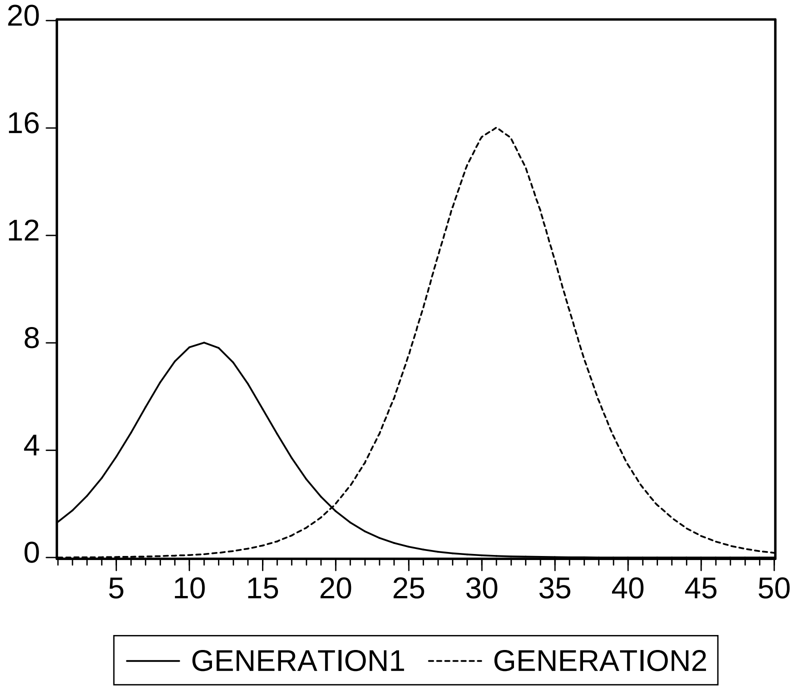

Figure 3: The two generations of adoptions which constitute the adoptions in Figure 2

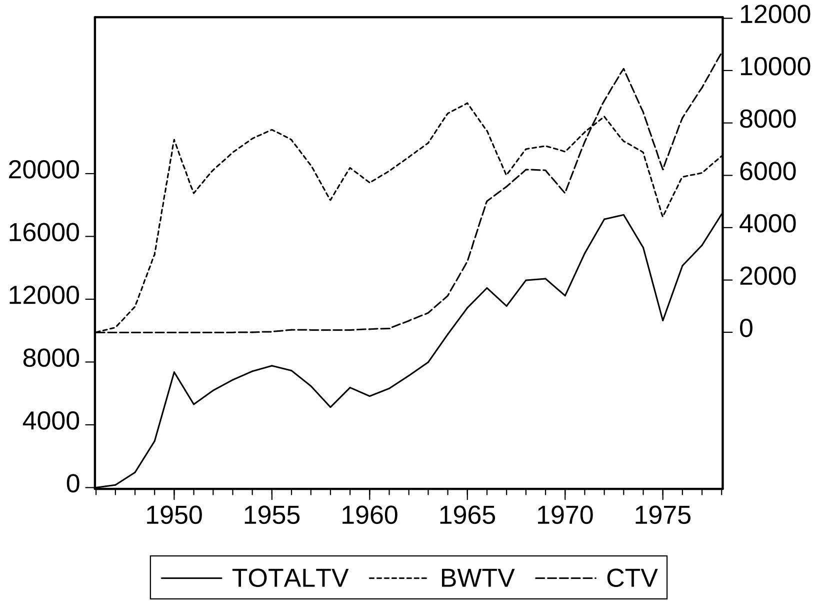

Figure 4: Two generations of televisions

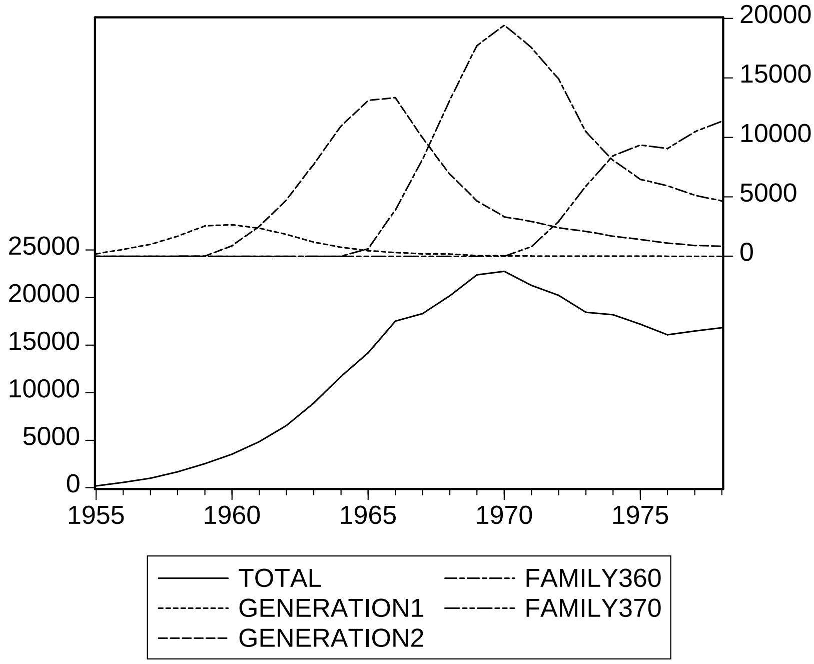

Figure 5: Four generations of IBM computers

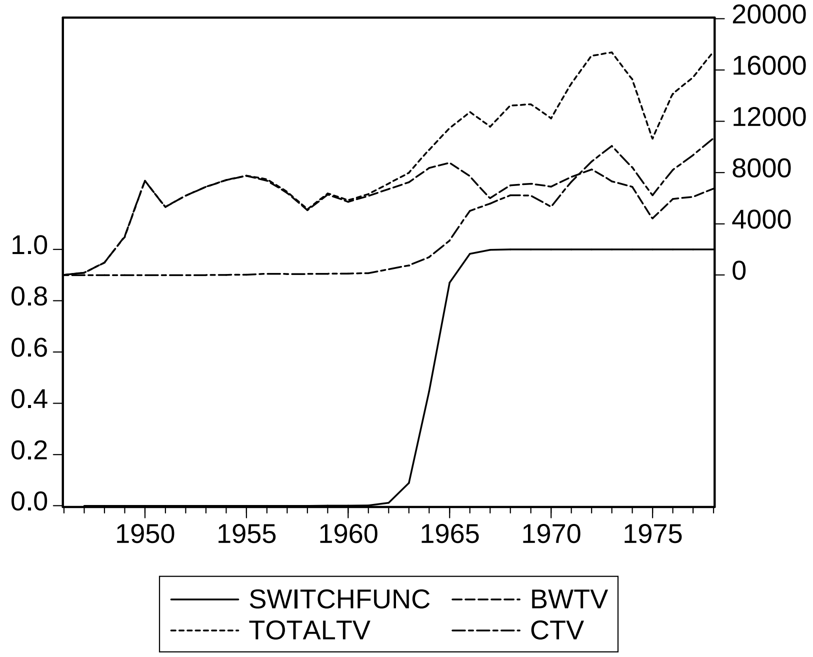

Figure 6: Two generations of televisions and the estimated switching function

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