FOCUSING ON THE GROWTH RATE OF TECHNOLOGICAL ADOPTION

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ABSTRACT

Models of substitution and adoption of consumer durable technologies typically focus on the level of adoption or the level of cumulative sales of the product. Although these variables may be of interest, decisions on market entry and the judgement of future return on investment are linked to the rate of change in adoption level. The percentage change in the current level of adoption, the growth rate, is more relevant, more meaningful and more sensitive a measure of past and future trends than is the level itself. This is an appeal for system modellers and forecasters to focus their attention on growth in studies of technological diffusion.

1. INTRODUCTION

Intuitively it is appealing to make analogies between the growth in popularity of a new technology and the spread of an epidemic. It is common to talk of something new "catching on". The growth in adoption of a technology can be thought of as a diffusion process, which has probably been stimulated by some favourable change in the business environment. If this change stimulates sufficient innovative purchasers to adopt the new technology they will influence others to copy them and to set growth in progress. Bass(1969) introduced a plausible model of this type. The historical analysis of many successful technologies' patterns of growth tends to confirm these notions. Of course, data on unsuccessful technologies is not available over a long time span.

Models of technological adoption usually focus attention on prediction of the level of adoption, or the surrogate measure of the cumulative sales. Looking back in time over various innovations, characterisically a sigmoid curve appears to describe the behaviour of the adoption level graph. The graphs are so convincing that otherwise experienced forecasters are apt to cast an uncritical eye over extrapolations of these curves into the future. As a result, decision makers may be convinced of the existence of a known and predictable saturation level toward which the curve of adoption level often seems to be heading. It is not difficult to show that these extrapolations of sigmoid growth curves can be seriously in error. But if mistakes are being made it is also necessary to show the cause of the error. This is the problem tackled in this paper.

2. INFLUENCES ON GROWTH

Once the growth of the market for a new durable product is set in motion the future changes in adoption level can be attributed to a few strong influences. Firstly, those people who have adopted the product influence others, who have not, to imitate them. This is a positive influence to buy and as a result of this influence the market for the product grows. Secondly, the proportion of possible adopters who have not yet bought the product will tend to decline as possible adopters become actual adopters in the process of imitation of others. The rate of adoption at any time will be a function of these two factors: it will be an increasing function of the number of adopters and a decreasing function of the proportion of actual versus possible adopters.

But the number of possible adopters is not fixed in a changing business climate. As the business climate changes so too the number of people who are in a position to purchase the product will alter. Were conditions to be fixed for all times it is clear that the level of possible adopters would fall and the level of actual adopters would rise by an equal amount to an equilibrium level. This equilibrium level would be the long term demand for the product. The adoption-diffusion-imitation process represents the delayed adjustment of demand to this equilibrium level. In practice the equilibrium demand will be price-sensitive and price itself will reflect business conditions as they fluctuate through the cycle and the seasons. But real price will also show the steady influence of the accumulated experience of manufacturers as more units are produced. This cumulative production experience will push down costs (a phenomenon noted by Arrow,1962) and prices will be driven lower in a competitive environment. As the real price falls so the number of possible adopters will rise. The 'equilibrium' demand will steadily increase in such a situation.

There are, of course, other influences in operation. The link between current adoption level and adoption rate is not a simple one. Implied here is the ability of adopters to diffuse within the possible adopter population so as to induce imitation. In the early stages of growth the chance of contact between each new adopter and those who may imitate him is relatively high. But should adopters tend to cluster then new adopters will be less effective in their influence. Adoption rate will be a non-linear function of the number of adopters in this case. The discard of old units is an example of past behaviour influencing the future. The past adoption level will influence the current rate of discard of units and adopters who are considering scrappage of their units form part of the possible adopter population.

The current business environment will affect both adoption and discard rates. An influence on the environment is the industry's own forecast of growth. When this does not marry with current behaviour there will be under or over supply and then price adjustment. Finally the emergence of a substitute technology will drain the level of possible adopters by removing those who are attracted to the substitute by reason of cost, convenience or fashion.

3. MODELLING THE RELEVANT VARIABLE

The foregoing discussion has indicated that the growth pattern of a technology is a complicated process involving non-linear and lagged dependencies together with fluctating disturbances from the business environment. One might wonder how it is that rather simple models of adoption level, such as the logistic and the Gompertz curves, have been used to describe this process. The reason is that these sigmoid models have been used to describe the level rather than the rate of growth of the level. Further, such models have fitted historical data but the relevant question for policy makers is the behaviour of the process in the future. It is not difficult to show that such models are not reliably extrapolated, and this will be demonstrated below.

To begin the discussion it will be helpful to review sigmoid models. In the course of this review, which will concentrate on a particular class of sigmoids, a heuristic argument will be developed to show that a sigmoid can describe the long term expected behaviour arising from the influences of imitation by purchasers and experience of manufacturers. The present approach differs from that of Bass(1980) who incorporated the experience effect in a modification of his earlier work (Bass, 1969). It is not the purpose of the present work to provide a genereal review of growth curves and the interested reader is referred to a recent paper by Meade(1984) for an appraisal of these models.

The growth in adoption of a technology, by analogy with the growth of a biological system, can be modelled by the equation:

$$\frac{dS}{dt} = r\,S\,(1 - \frac{S}{A}) \qquad (1)$$

In this equation S is the level of adoption, r is the initial rate of growth of the level, and A is an equilibrium level which is approached asymptotically. Sometimes S is taken to be the level of cumulative sales, which is a surrogate for the adoption level. When the level S is well below the asymptotic value A equation (1) describes linear feedback as the current adopters influence others with an effectiveness (a probability of imitation) proportional to their number. The fraction of unsatiated demand is (1 - S/A). As the level S increases so this fraction decreases and the rate of growth slows. If A is treated as a constant equation (1) integrates to give a logistic curve for S. This is a sigmoid which is symmetric about its point of inflection, which is the point at which dS/dt is a maximum.

The symmetric logistic curve is not sufficiently flexible to represent the range of growth patterns observed in practice. Realising this, Easingwood et al. (1981) suggested a modification which allowed for a parameter to model asymmmetric growth. But it will be shown below that asymmetric growth can be introduced naturally by a generalisation of the logistic to include the effects of experience. The argument differs in important respects from that of Sharp(1985).

Equation (1) describes the approach of adoption level to an asymptotic equilibrium, A, which can be thought of as an equilibrium demand. This description applies to a static equilibrium demand, but business conditions are known to change and it can be presumed that the value of A will also vary. An important cause for change is the feedback mechanism which links cumulative experience in production of a technology to cost reduction and, in a competitive market, to price reduction. As prices fall so more people will be able to buy the product. They will not do so immediately because awareness of the technology must first spread; the gradual adjustment to equilibrium is described by an equation such as (1). The price in this discussion is the real price of the product (deflated by an appropriate index) and the downward price trend is a long term average behaviour. This phenomenon has been documented by the Boston Consulting Group (1968) and Dino (1985) has made empirical analyses of electronic products recently.

The relationship between long term demand and price is likely to be of the form

$$A \propto p^{-\eta} \qquad (2)$$

where $\eta > 0$ measures the price elasticity of the equilibrium demand. Price itself is expected to decline as manufacturers improve production methods and costs fall. The empirical evidence suggests a relationship of the form

$$p \propto S^{-\lambda} \qquad (3)$$

where S has been taken to be proportional to cumulative experience. The existence of such an experience curve closes the feedback loop between the equilibrium level A and the current level S to give

$$\frac{S}{A} \propto S^{1-\lambda\eta} \qquad (3)$$

The concept of an equilibrium demand is now best replaced by the idea of a target level, a, so that

$$\frac{S}{A} = \left(\frac{S}{a}\right)^{1-\lambda\eta} = \left(\frac{S}{a}\right)^{\gamma} \qquad (4)$$

and now $\gamma = 1 - \eta\lambda$ is a parameter which allows the symmetry of the growth to be modelled. The inclusion of these effects in the simple model (1) results in the modified equation

$$\frac{dS}{dt} = \frac{b}{\gamma}\left\{1 - \left(\frac{S}{a}\right)^{\gamma}\right\} S \qquad (5)$$

In (5) the initial rate of growth is equal to b/γ. The equation can be integrated (for $\gamma \neq 0$) and the result is the generalised logistic:

$$S(t) = a\{1 + c\exp(-bt)\}^{-1/\gamma} \;; \quad c = \{a/S(0)\}^{\gamma} - 1. \qquad (6)$$

Different sigmoids are obtained for different values of γ. Recently McGowan (1986) noted that this generalisation does indeed improve the fit over the simple logistic. The simple logistic corresponds to $\gamma = 1$, in other words a negligible value for the product of parameters, $\lambda\eta$.

Ghemawat (1985) quoted typical experience curve slopes of around $\lambda \sim 0.85$ in a large number of academic studies. If it is assumed that some price reduction will result from experience then the simple logistic will apply only when $\eta = 0$, that is when the long term equilibrium demand is perfectly inelastic.

Equation (5) has been deliberately written in the form

$$\frac{dS}{dt} = - b\, f^{(\gamma)}\{\frac{S}{a}\}\, S\,, \qquad (7)$$

where

$$f^{(\gamma)}\{y\} = \frac{y^{\gamma} - 1}{\gamma}\,, \qquad \gamma \neq 0, \qquad (8)$$

in order to show that the right hand side of the equation contains a power transformation of the fraction of target $y = S/a$. If, when $\gamma = 0$, the transform is

$$f^{(0)}\{y\} = \log_e(y)\,, \qquad (8a)$$

then the transform given by (8) and (8a) is the same family of transforms introduced by Box and Cox (1964) to stabilise the variance of nonlinear data. This suggests that equation (7) could be written in terms of the time derivative of log(S) :

$$\frac{d}{dt} \log_e(S) = - b\, f^{(\gamma)}\{\frac{S}{a}\}\,. \qquad (9)$$

Equation (9) recommends itself on both heuristic grounds and statistical grounds as being a suitable starting point for the analysis of the non-linear data observed in the adoption of new technologies. The important difference between equation (9) as a starting point for analysis and equation (6), which describes a level, is that in (9) the dependent variable is the rate of change of the logarithm of level, usually referred to as a growth rate. Not only is growth rate a more stable quantity in statistical terms, it is also more relevant to a decision maker because it is the same type of variable as a cost of capital, a wage inflation rate and so on. In other words the growth rate can be compared directly with the rate of return on investment and the rate of cost inflation in order to assess the future direction of policy.

It should not be thought that equation (9) represents a complete description of the growth in adoption. Quite clearly most of the influences discussed in the previous section have been ignored in deriving the equation. Also there has been no attempt to include chance effects. What is described by equation (9) is the most probable path of growth rate for a process of technological adoption in which imitation and experience effects dominate and in which other influences are equally likely to push growth rate up or down. The usefulness of such a model lies in its ability to illuminate the past, to clarify the present and to make explicit the assumptions behind predictions of the future. It is argued here that an analysis of growth rate is able to do this whereas an analysis which emphasises the level of adoption is not.

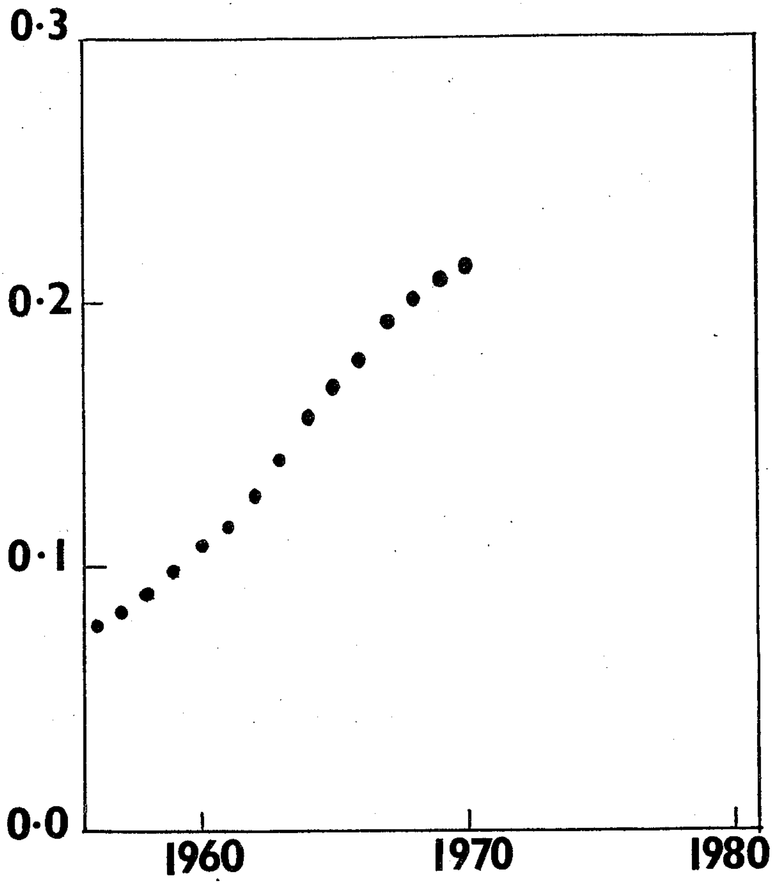


FIGURE 1. Cars per capita in Britain to 1970.

The reader is invited to judge upper and lower limits for the future course of the adoption curve.

4. A PRACTICAL EXAMPLE.

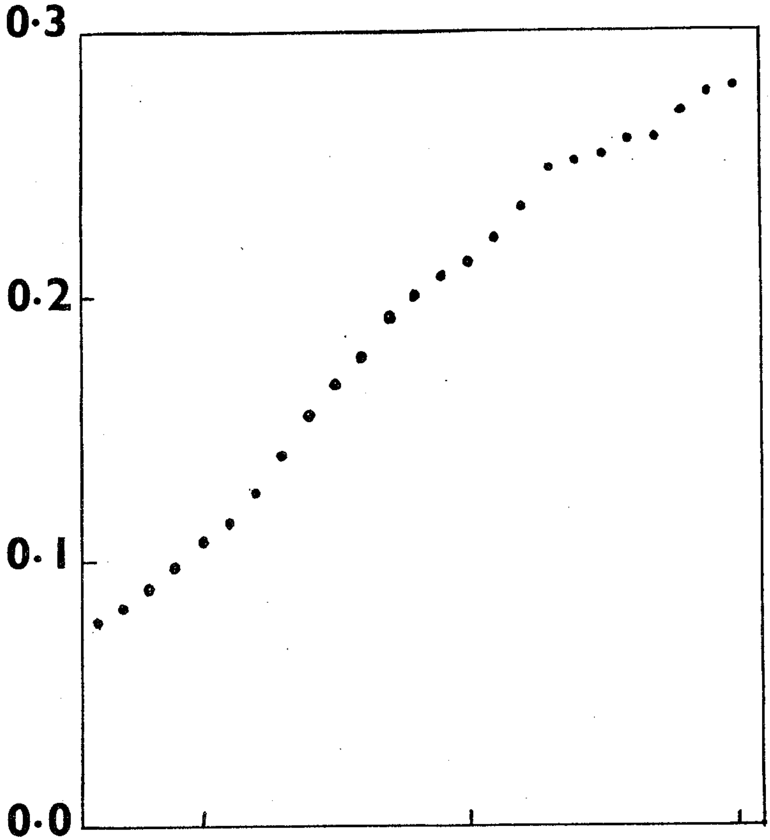
It will be helpful to look at an example of technological adoption in practice. The case considered is the adoption of private motor cars in Great Britain. The data consist of the number of cars per head of population. This quantity is computed from the U.K. government's official statistics on population and on cars currently licensed, to be found in the publication 'Economic Trends', for example.

Forecasts of the number of cars per capita influence policy decisions for national transportation planning, road construction and so on. In Britain the number of cars per capita has been increasing but the rate of increase has shown signs of declining. The data up to 1970 are shown in Figure 1. Before proceeding with the discussion, the reader is invited to examine Figure 1 in detail, without reference to the other figures in the paper. The adoption curve of Figure 1 certainly has the sigmoid form so characteristic of a saturating market. The reader should attempt now to sketch on the figure his judged extrapolation of the data, in particular, to mark upper and lower limits to the pattern of adoption for the next decade.

The actual course of events for the next decade is shown in Figure 2. Most readers who have not seen this data previously will be surprised by the pattern of adoption which actually ocurred. It is worth while checking back on the simple extrapolations suggested above to see the extent of any discrepancy. More sophisticated extrapolations of the curve, based on some weighted least-squares criterion for example, are unlikely to give more correct results. Meade(1985) has suggested an adaptive sigmoid fitting procedure based on the Kalman filter and Harvey(1984) has suggested a local sigmoid trend-fitting procedure. These adaptive approaches will give adjusted forecasts as new data becomes available but at any point in time they represent an extrapolation of the adoption curve which is similar to that produced by eye.

It is necessary to examine the rate of growth of the adoption curve in order to see why the growth pattern appears clear up to 1970. The percentage growth over each year is shown in Figure 3. It is seen from this figure that there was a steady downward trend in the years before 1970 and this is the reason for the smooth appearance of the graph of adoption level up to that time. But whereas one might be confident in extrapolating Figure 1, incorrectly, the growth rate data shows that there is noise affecting the long term trend and so the extrapolation would be made with more care. It would also be suspected from examination of Figure 3 that the changes in growth are linked to the business cycle. Judgements of future business trends are likely to be expressed in terms of rates of interest, or rates of price or cost inflation, and so on. These judgements are more naturally incorporated within a forecast of the rate of growth in adoption level. From these comments it would appear that extrapolations of the curve of car adoption level made during the 1970s would be doomed to failure. In fact Brooks et al.(1978) showed that such forecasts were self-contradictory.

FIGURE 2. Cars per capita in Britain to 1980.



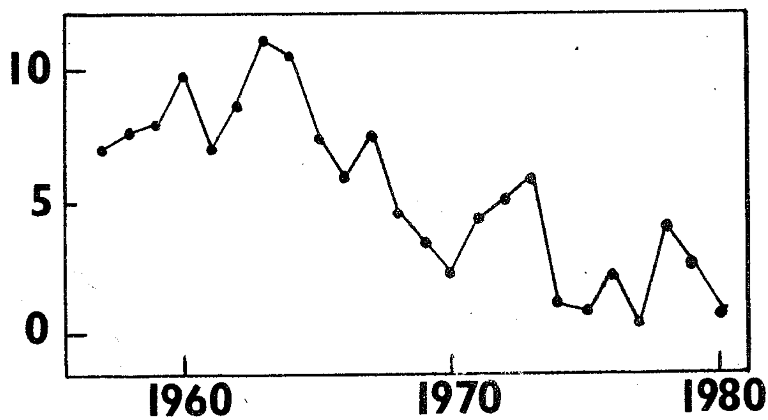


FIGURE 3. Percentage Growth over year for data of Fig. 2.

5. CONCLUSIONS

Models of technological adoption should focus on the growth rate of the adoption process. If growth rate is correctly modelled the adoption level, which is often taken as the main object of the study, will follow. Models which concentrate on the adoption level can miss the importance of the patterns of consumer behaviour which changes in growth rate reveal.

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