Journal of Scientific & Industrial Research
Vol. 66, April 2007, pp. 299-304

Managing uncertainty in forecasting the diffusion of telecommunications innovations

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Received 01 September 2006; accepted 30 November 2006

The study presents how adding more independent explaining variables and applying neural networks for forecasting purposes could improve the forecasting accuracy of the diffusion of innovations. The paper proposes a set of uncertainty sources of telecommunications industry that have notable affect on the diffusion of innovations in the field. Diffusion patterns and uncertainty indicators of 81 countries were classified using self-organizing map neural network approach, and the results indicate that various levels and types of uncertainty are likely to produce different types of diffusion patterns.

Keywords: Cellular subscriptions, Diffusion of innovations, Neural networks, SOM, Telecommunications, Uncertainty

Introduction

Telecommunications markets are characterized by rapid changes. Mullins & Sutherland[1] defined rapidly changing markets "as those in which the pace of innovation is such that new-to-the-world products are brought to market frequently, at least biannually". The changes causing uncertainty are evolving rapidly at all levels of public policy, business organizations, and consumers[2]. Uncertainty[3,4] is related to change and unpredictability in the objective characteristics of the environment external to the organization. March & Simon[5] defined uncertainty as a lack of internal control, and proposed internal structural techniques to reduce impact of uncertainty on organizational equilibrium. Uncertainty that confront firms operating in rapidly changing markets are: i) Macroeconomic level; ii) Industry level arising from business characteristics; iii) Cultural level arising from cultural differences between countries; and iv) Microeconomic level arising from consumer behavior and customer needs. Neural networks (NNs) could act as valuable tool for forecasting the diffusion of new-to-the-world products or services, and thus also for management of prevailing uncertainty and risks.

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Sources of Uncertainty in the Diffusion of Telecommunications

Importance of Uncertainty Variables in Diffusion Forecasting

The effects of advertising have been studied[6-9] and some studies[10-12] have included consumers' price expectations into the diffusion models. Jones & Ritz[13] studied the effects of distribution on diffusion. But all these attempts have never been able to describe the overall role of different factors affecting the diffusion of innovations. However, all these factors are product-market specific, and are controllable by the marketer. Although these studies provide valuable information on diffusion processes, they are not suitable for forecasting[14]. Using analogies by calculating estimates of the parameters for the analogies and regressing these estimates against various factors, like macroeconomic and micro level factors, are likely to affect the diffusion process[15]. Frank[16] found that in macro level, in Finland, the economic situation had a significant effect on the diffusion of cellular subscriptions. This study suggests use of NNs instead of regression analysis for finding the relationships between diffusion parameters and product or market characteristics.

Macroeconomic and Industry Uncertainty

The mobile communications industry's[1] exceptionally fast growth is based on the increasing information intensity of economic activity and the globalization of capital flows, manufacturing and trade that have resulted in strong demand for better, more varied and less costly communication and information services[17]. Also, technological developments, and development of common standards and deregulation have led to declines in costs of both transmission capacity and switching, thereby investment costs of connecting a mobile subscriber have declined[18]. In turbulent and uncertain environment, management faces uncertainty about how much capital to invest in pursuit of rapidly changing markets as well as when to invest. Other indicators for industry uncertainty are the number of bankruptcies, and the pace of number of new models introduced within a year. In a short run, fluctuations in stock rates may also indicate the level of uncertainty related to industry. Macroeconomic uncertainty is likely to inhibit diffusion, and it stems from financial, technological, social and political situation in a country. Macro level diffusion of a new telecommunications product or service is dependent on a multitude of market- and product-related factors that interact in a complex set of relationships, which are often nonlinear, and difficult to specify. Furthermore, empirical data about the factors is abundant, but often noisy and incomplete. These problematic characteristics favor the use of NNs instead of traditional statistical methods in finding suitable analogies for forecasting the macro level diffusion curves.

Cultural Differences

Hofstede[19] identified the uncertainty avoidance, which is defined as “the extent to which the members of a culture feel threatened by uncertain or unknown situations”. Risk taking is an important factor, which is usually associated with entrepreneurial activity. But also consumers take risks when they try a new product. Cateora & Ghauri[20] observed societies having relatively similar scores on the value dimensions tend to respond in a similar fashion. Gatignon & Robertson[21] noted that the diffusion rate and the maximum penetration level are positively related to the innovation’s compatibility with social values. Thus, it is proposed that the level on country’s uncertainty avoidance affects country’s adoption process and the speed of diffusion within a country.

Adoption Behavior

A key success factor of new product introduction is the identification of those people who are the first to buy the product or service launched into markets[22]. It is necessary that the innovation is adopted by these “first” individuals who are characterized as having high level of innovativeness[23]. The high technological and market turbulence increases consumers’ perceived risk of adopting new services. Sundqvist *et al*[24] found that higher the perceived risk, slower the diffusion within the country, and that earlier the country has adopted the wireless communications, slower the diffusion process.

Neural Networks in Diffusion Research

Basic Idea and Advantages of Neural Networks

NNs attempt to mimic such useful functional capabilities of the brain as abilities to understand and simplify or generalize a complex set of inputs, to handle problems of high dimensionality and reduce them to lower more manageable proportions, and to associate complex patterns and cope with defective or distorted data[25]. NNs can be divided in three broad classes: a) Data filtering networks are applied in pattern recognition and optimization problems; b) Classification networks or self-organizing maps can be used as an alternative to cluster analysis; and c) Prediction networks using supervised learning can be used in time series forecasting problems or as an alternative to regression or discriminant analysis[26.] Advantages of NNs over traditional statistical methods are follows: i) NNs do not require a priori assumptions of the form of relationships between variables[27]; ii) NNs can identify linear as well as nonlinear relationships; iii) NNs with a hidden layer can approximate any function; and iv) NNs are less sensitive than statistical methods to noise, outliers or missing values in the input data[28]. NNs can also handle discontinuities and apply different functions in different sections of the data[29]. NNs, which process data effectively in a parallel and distributed way, are capable of handling large amounts of data. The most serious disadvantage of NNs is the lack of explanatory or diagnostic qualities, besides lack of formal guidelines for the design and configuration of network, so it has to be done by trial and error for each specific problem.

Neural Network Applications in Business Forecasting

Adya & Collopy[30] identified 48 studies (1988-1994) that used NNs for business forecasts and predictions. Wong *et al*[31] found 49 studies (1994-1998) of forecasting applications in finance and marketing. Multilayer feedforward networks can be applied for causal problems using independent

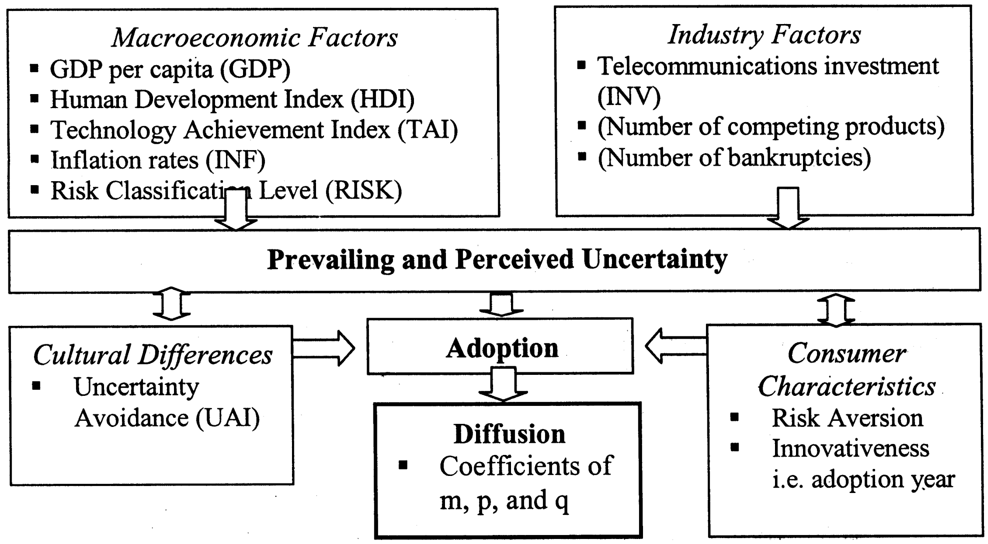

Fig. 1— Factors affecting uncertainty in diffusion forecasts in telecommunications

variables as inputs and dependent variable as output, or extrapolative problems using past observations as inputs and future value as output. There are relatively few applications in macroeconomics, partly because of the data is often low-frequency time series data with small samples[32]. A number of comparative studies on the performance of NNs and time series methods like Box-Jenkins and linear regression[33,34] suggest that NNs are superior with nonlinear problems, multivariate time series forecasting problems with multicollinearity and outliers, monthly and quarterly data with seasonal variations and discontinuities, and when the forecasting horizon is long. NNs are less accurate for short-term forecasting of a series with a long history of annual data.

Possibilities for Diffusion Forecasting

Diffusion forecasting data includes time series of varying lengths from different countries describing cumulative adoptions of various products or services and development of the factors that are assumed to influence the number of adoptions. Self-organizing maps could provide useful information for finding suitable analogies, if the post hoc estimates of diffusion parameters (market potential and coefficients of innovation and imitation) were used for classifying diffusion types on one hand, and uncertainty indicators on the other (Fig. 1). Another approach is the supervised learning network, which could be used in a causal and cross-sectional way, where uncertainty indicators measured at the time of launch are used as inputs for the net. The output variables could be the post hoc diffusion parameters.

Empirical Research

Data and Measures

Data includes ITU database[35] for the annual number of adopters of cellular subscriptions. Indicators for human development and technology achievement index were obtained from United Nations Development Report[36]. Macroeconomic uncertainty was measured by gross domestic product per capita (corrected by purchasing power parity), inflation rates, human development index, technology achievement index, and country risk index (obtained from PRS Group[37]). Uncertainty prevalent in wireless communications was measured by annual investments in telecommunications per capita. Number of competitors would also have been a good indicator but unfortunately the data was not available. To measure microeconomic and cultural uncertainty, Hofstede's cultural dimension of uncertainty avoidance, was applied. Innovativeness was measured by the country's adoption year of the analogue mobile phones. Uncertainty measures were used from the year of mobile phones adoption, but in some cases data was not available and more recent figures were used.

Analysis and Results

Bass[38] concluded that an innovation would diffuse because of spread of information between adopters and from the mass media to adopters as

$$y(t) = \frac{m \cdot \left(1 - e^{-(p+q)\cdot t}\right)}{1 + \frac{q}{p} \cdot e^{-(p+q)\cdot t}}. \qquad \ldots(1)$$

where y = number of cumulative adopters, and t = point of time, m = upper asymptote of the function, and thus the final number of adopters. Bass sees the diffusion as a communication process, where the adoption is due to innovativeness (p) and imitation (q). Both p and q, have effect on the shape of diffusion curve; smaller values are the point of innovation's sales peak. Diffusion patterns were classified into four distinct categories using the Kohonen self-organizing map NN approach (Appendix 1). Diffusion parameters were only available for 44 countries, since the Bass model failed to converge in 18 cases, and diffusion data was not available for 19 countries (Table 1, Fig. 2). Most typical pattern can be seen in Diff1, which will reach its final mobile penetration rate (81%) within 19 years from launch. In Diff2, diffusion starts very slowly, but there will be more than two subscriptions per inhabitant within 20 years from launch. Diff4 will reach a penetration rate (58%) within 12 years, and in Diff3 the final penetration will remain very low, although it is achieved quite fast.

In order to examine the effects of prevailing uncertainty, another NN classification of 81 countries was made (Table 2). The first group represents lowest level of uncertainty with high levels of technological advancement, human development, telecom investments, and purchasing power, while inflation, country risk and uncertainty avoidance are low. Uncert2 consists of relatively wealthy and advanced countries with an uncertainty- avoiding culture. Uncert3 and 4 consist of less developed countries and are rather similar to each other, except for the extremely high inflation rate in the former.

In order to see if the various patterns of uncertainty are more likely to foster certain types of diffusion. Contingency table (Table 3.) shows the number of countries in each combination of diffusion and uncertainty patterns. The association is statistically significant (third column with only one case was removed, chi square test of independence χ^2=14.55, d.f.=6, sig.=.024). Low uncertainty (Uncert1) is most likely to coexist with a slow diffusion of mobile communications to a high maximum penetration. Second group consisted of relatively affluent societies with an uncertainty avoiding culture. These countries have adopted mobile communications 5 years later than countries in the previous group, and their maximum penetration (60-80 %) will be reached faster. Less affluent hyperinflation countries in the third group had only one case of diffusion data available, so no conclusions about likely diffusion

Fig. 2— Typology of mobile communications diffusion patterns

Table 1— Classification of mobile communications diffusion patterns

Group	No. of countries	m	p	q	Examples
Diff1	27	0.81	0.0004	0.6587	France, Estonia, Israel
Diff2	5	2.47	0.0001	0.4934	Ireland, Denmark, Sweden
Diff3	2	0.11	0.0068	1.4461	Colombia, Panama
Diff4	10	0.58	0.0006	1.0850	Korea, Slovenia, Chile

Table 3— Classifications by diffusion pattern and uncertainty

	Uncert1	Uncert2	Uncert3	Uncert4	Total
Diff1	11	11	1	4	27
Diff2	5				5
Diff3		2			2
Diff4	1	8		1	10
N.A.	7	12	2	16	37
Total	24	33	3	21	81

Table 2— Country classification by levels of uncertainty

Group	No. of countries	TAI	HDI	UAI	INF	INV	GDP	Year	Risk
Uncert1	24	0.62	0.89	53	2.7	150	25409	1985	87
Uncert2	33	0.37	0.79	76	8.2	53	8757	1990	73
Uncert3	3	0.28	0.68	69	113	31	4083	1990	54
Uncert4	21	0.19	0.58	65	8.7	23	2839	1989	64

patterns can be drawn. Same problem applies to the poorest countries in Uncert4, although 5 diffusion cases were available and they concentrated on the first diffusion pattern.

Conclusions and Further Research

Macroeconomic uncertainty and cultural attitude to risk avoidance are significantly related to the diffusion of mobile communications, and can be used for finding suitable analogies for predicting the diffusion pattern in less innovative markets. Countries need to have a certain set of background characteristics in order to have the most favorable circumstances for diffusion of telecommunications innovations; in addition to wealth and low political and financial risks, the country has to be risk tolerant. Availability of more data in analysis of diffusion of wireless communications will be advantageous because neural networks are better realized with large data sets. Zotteri & Verganti[39] proposed that as demand becomes complex, a possible approach for managing such uncertainty is to collect information directly from customers. Also, it would be beneficial to incorporate more specific data on the competitive situations, prices, levels of promotion etc.

Appendix 1— Training algorithm in Kohonen Network (Neural Connection 2.0 User's Guide, pp. 241-243 & 254-255)

Kohonen Network is an unsupervised neural network that produces a self-organized map of the data presented to it during training. In unsupervised learning, network is presented with the set of training inputs, and it creates its own representation of input data based on common features in the data. Kohonen networks are constructed from a layer of nodes (neurons), each of which is connected to all input fields. Connections between nodes and inputs have an associated weight. For competitive unsupervised learning, neurons are organized into groups. Neurons in each group are connected together so that if one neuron gives a high level of output, it tends to inhibit outputs of other neurons. Thus, neurons in each group compete with each other for the right to represent a particular feature. Once a particular neuron in the group begins to respond more strongly to a particular input, it suppresses its neighbors and thus wins competition. Eventually, each cluster of neurons comes to represent different features in the data. The calculation associated with Kohonen network can be split into two parts: i) Building the model; and ii) Using the model. The training algorithm for building the model is as follows: When presenting an input pattern X_p, composed of input elements $x_1, x_2, \ldots, x_n$, to a Kohonen network with n input nodes, the weight between an input i and a node j is given by w_{ij}.

Training Algorithm

1. Initialize the weights between inputs and the nodes.
2. Present an input $X_p = x_1, x_2, \ldots, x_n$.
3. Calculate the error measurement between the input and the weights, in this case using Euclidean distance

$$d_j = \sum_{i=1}^{n} (x_i - w_{ij})^2$$

4. Select the node $\boldsymbol{j^*}$ that has the minimum value of $\boldsymbol{d_j}$.
5. Update the weights for node $\boldsymbol{j^*}$ and its neighbors to be

$$w_{ij}* = w_{ij} + \eta(x_i - w_{ij})$$

where η is learning rate of Kohonen layer, and typically decays over time. The neighborhood size is defined before the model is built, and again typically decays over time.

Repeat steps 2 to 4 until the weights have stabilized.

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