

# The Effects of Network Externalities on the Diffusion of Cellular Telephones

NIGEL MEADE, TOWHIDUL ISLAM



*Nigel Meade is Professor of Quantitative Finance at Imperial College, London, UK*



*Towhidul Islam is Associate Professor, University of Guelph, Canada*

In a country with a supply restricted fixed line telephone network, we might expect a rapid diffusion of cellular telephony as an alternative means of communication becomes available. However, in developing countries, long take-off times are observed giving a left hand skew to the diffusion curve. The delay in take-off can be attributed to network externalities, such as difficulties in establishing links between cellular and fixed line networks. Another explanation is that the typical diffusion curve of an interactive technology is left skewed compared to a non-interactive technology, because a critical mass of users is needed before take-off can occur. To investigate the existence and causes of left skew, we use data from 70 countries covering all geographical regions and economic categories with a comprehensive set of economic, cultural and telecommunications variables to measure the evidence for left-skew. We use Bemmaor's (1994) gamma shifted Gompertz skew parameter to investigate network externality. The power of economic and cultural covariates to explain the variation within skew measures is explored and the implications of left-skew on forecasting accuracy are discussed.

## 1 Introduction

The motivation for adopting a cellular telephone is the desire to communicate in a convenient way with other subscribers to the cellular network and to the fixed line network. As the digital generation was introduced, this motivation was stimulated further by capabilities such as communication by text messages. Thus the diffusion of this interactive technology may be distinctive as its adoption depends, to some extent, on the perceived number of previous adopters. A number of recent innovations such as electronic data interchange (EDI), video conferencing, videotext, electronic fund transfer (EFT), email and fax connections are other examples of interactive technologies.

Direct network externalities are a quality of certain goods and services that become more valuable to a user as the number of users increases. According to Economides (1991), network externalities occur when the buyer of the last unit of the good has a higher benefit than the buyer of the first unit because the sale of the earlier units has created extra benefits in a related dimension. Allen (1988) puts it another way, prospective subscribers perceive more value as the subscriber pool grows, thus the utility of an interactive technology depends on the size of the user community. Mahler and Rogers (1999) define critical mass as the minimal number of adopters of an interactive innovation for further adoption to be self-sustaining. Rogers (1995) explains adoption prior to the achievement of critical mass in terms of a few individuals with an almost zero threshold to innovation, these individuals are so venturesome that they will adopt a new idea before anyone else in their system has adopted.

It is also possible to have indirect network influences such as: supply side network effects (see Schoder,

2000); passing benefits to adopters from manufacturers (or service providers) due to returns to scale (eg. low price); availability of related products, for example the utility of each DVD player increases as more DVD titles become available (Hauser et al., 2005; Gupta, Jain and Sawhney, 1999).

Lim, Choi and Park (2003) investigated the effect of direct network externalities using sales take-off times and found late take-off in the diffusion of fax services in US and Korea. Mahler and Rogers (1999) suggest that the typical diffusion curve of an interactive technology is left skewed compared to a non-interactive technology, "the rate of adoption does not takeoff in the familiar 'S' shape until a critical mass of the adopters has been reached". A number of recent papers have identified the importance of network externalities on technology diffusion. Schoder (2000) maintains that with "strong network effects it is not possible to forecast the success of telecommunications services with a high degree of confidence". Hauser et al (2005) identified understanding the role of network externalities in determining the timing of take-off and the subsequent growth in diffusion as an important research challenge. Mahler and Rogers (1999) advocated testing for the effect of direct network externalities on the diffusion of new telecommunications services, rather than assuming it exists.

With these latter comments in mind, we shall investigate the existence and effect of direct network externalities on the diffusion of cellular telephones. We propose to measure the evidence of direct network effects using Gamma-Shifted Gompertz (G-SG) model, (see Bemmaor, 1994 and Bemmaor and Lee, 2002).

The paper is laid out as follows. In Section 2, we will describe three research questions relating to direct externalities and review the literature on the determinants of take-off times and the G-SG model. In Section 3, we briefly describe the technology and the data set. Section 4 contains the analysis of the data including the measurement of take-off times and the fitting of the G-SG model. Section 5 is our summary and conclusion.

## 2 Research Questions and Literature Review

In this section, we will posit three research questions relating to externalities in the cellular telephone market. The last part of this section describes the diffusion model used, the gamma shifted Gompertz.

### 2.1 Do Cellular Telephones Exhibit a Direct Network Effect?

Some authors are skeptical of the argument for critical mass in telecommunications diffusion. Allen (1988) argues that each new subscriber adopts as an individual joining all of the existing subscribers. Mahler and Rogers (1999) suggest that diffusion of cellular mobile telephones did not face the externality problem of interactive telecommunication, as mobile phone adopters connected to the existing base of all fixed telephone users and therefore achieving critical mass was not an issue. Both arguments are plausible for the telecommunications markets of developed nations but not necessarily true for the developing countries. A large proportion of the world's fixed telephone markets can be characterized as supply restricted and over 100 countries have waiting lists (see ITU Database 2004). In many developing countries, it took several years to establish network connections and tariff sharing arrangement between fixed telephone and cellular networks. In some countries, early cellular telephones were provided by fixed line monopoly operators as value added services (Madden et al. 2004). The subsequent growth of competition and the timing of the entry of competitors might explain some cases of rapid diffusion of cellular telephones. Both these scenarios lead us to expect to see skewness, as evidence of the delay until critical mass is achieved, in the diffusion of the first generation of analog cellular telephones in developing countries.

In the case of digital technology, the significant development was the availability of data services; for example, the short messaging service (SMS), which allows text messages and e-mail to be sent between mobile handsets. Thus for digital, these benefits will increase with network size and we expect to see skewness caused by these network externalities in the diffusion of cellular telephones; however since analog is established, we expect the effect to be similar across different economic sectors.

### 2.2 In the Presence of a Network Effect, which Covariates Explain Inter-Country Differences in Skew Coefficients

In 2.1, we hypothesize that network effects may be explained by the level of economic development of the country. In addition to the economic effect, we investigate whether cultural variables influence the skew of analog adoptions. Wealth is an obvious determinant of the ownership of a consumer durable and determinant of earlier adoption. A number of researchers (eg. Sundqvist, Frank, and Pumalainen 2005, Desiraju, Nair, and Chintagunta 2004, Putsis et al. 1997, Rogers 1995, Talukdar et al. 2001) have shown the impact of wealth on adoption decisions. Analog cellular diffusion will be negatively impacted by presence of poor network conditions and supply restrictions of fixed telephone networks. Islam and Fiebig (2001) (see their Table 1, p. 252) have shown that the extent of supply restrictions and poor network conditions characterize membership of economic categories. The covariate, the number awaiting main lines as a percentage of the number of fixed telephone connections, used by Islam and Fiebig (2001), is highly negatively correlated to GDP per capita (for the current sample it is  $-0.58$ ).

Prior research strongly suggests that a country's culture influences new product adoptions (eg. Van den Bulte and Stremersch 2004, Everdingen and Waarts 2003 and Steenkamp 2001, Steenkamp, Hofstede, and Wedel 1999, Yaveroglu and Donthu 2002, Takada and Jain 1991, Kumar, Ganesh, and Echambadi 1998, Dekimpe et al. 2000, Gatignon et al. 1989). Yaveroglu and Donthu (2002) and Steenkamp et al (1999) find a negative association between a country's uncertainty avoidance and its innovativeness. In high uncertainty avoidance cultures, their risk averse attitude implies that people will not take unnecessary risks and only adopt innovations if their value has already been proven in the market.

In addition to economic and cultural variables, the relative geographical location of countries is believed to affect innovation diffusion rates (see Hagerstrand 1967, Craig et al 1992, Ganesh, Kumar, and Subramanian 1997, Baptista 2000). The other important covariate is the lead time, the time delay between the first introduction of the technology and its becoming available in each country (see Takada and Jain 1991, Ganesh and Kumar 1996, Kalish, Mahajan, and Muller 1995).

Following the literature review, to the skew coefficient, we shall use an economic variable (membership of an economic sector), a cultural variable (the uncertainty avoidance index) and as control variables we shall use geographical regions and lag-lead time.

### 2.3 Does a Model's Forecasting Accuracy Improve if Direct Network Effects are Taken into Consideration?

Gupta, Jain and Sawhney (1999) found that modeling the diffusion of High Definition Digital TV (HDTV) without the effect of indirect network externalities led to biased forecasts. Schoder (2000) comments on the necessity of taking direct network externalities into account to enhance the accuracy of forecasts of the diffusion of telecommunications services. Both authors point out that biased forecasts can lead to costly strategic mistakes. We expect greater forecasting accuracy from the G-SG model than the Bass model which neglects network externalities, for the first (analog) generation of cellular technology.

### 2.4 Gamma-Shifted Gompertz Model

The Bass model (Bass 1969) is almost the default model of diffusion in marketing literature. It assumes that population homogeneity and social contagion underlie the theoretical dynamics that generate the S-shaped adoption curve. A number of researchers from several disciplines, marketing (eg. Bemmaor and Lee 2002, Bemmaor 1994, Van den Bulte and Stremersch 2004), sociology (eg. Granovetter 1978) and economics (eg. Russell 1980, Liebermann and Paroush 1982) have raised the possibility that the S-shape is due to heterogeneity between individuals. The heterogeneity may be due to differing thresholds to innovation, reservation prices or income elasticities. We shall consider a model which can accommodate individual heterogeneity and is also capable of modeling skew in data. This is the Gamma Shifted Gompertz (G-SG) model proposed by Bemmaor (1994). For recent applications of this model, see Bemmaor and Lee 2002, Van den Bulte and Stremersch (2004). Following Bemmaor (1994) and Bemmaor and Lee (2002), we assume that individual level model of adoption timing is consistent with a shifted Gompertz cumulative distribution as follows:

$$F(t) = (1 - e^{-bt}) \exp(-\eta e^{-bt}) \quad (1)$$

The coefficient  $\eta$  reflects the level of individual heterogeneity. For a fixed value of  $b$  (the scale coefficient), a lower  $\eta$  implies a lower mean time to adoption or a stronger individual propensity to buy. If  $\eta$  varies according to a Gamma distribution (with shape  $\alpha$  and scale  $a$ ), then the aggregate level cumulative adoption distribution of G-SG becomes:

$$F(t) = \frac{1 - \exp(-bt)}{[1 + a \exp(-bt)]^\alpha} \quad (2)$$

If  $\alpha=1$ , the model reduces to the Bass model and the Gamma heterogeneity distribution reduces to an exponential distribution. Smaller  $\alpha$  implies higher heterogeneity (the coefficient of variation of the

Gamma random variable is  $\alpha^{-0.5}$ ). When  $\alpha=0$ , the model reduces to an exponential distribution and when  $\alpha=\infty$ , it becomes shifted Gompertz, a left skewed distribution. The advantage of the G-SG model is its closed form solution and its nesting of the Bass model. However, this flexibility is achieved at the cost of an additional parameter.

Under the assumption that a critical mass is crucial for sales take-off in a developing country, adoptions may be expected to occur slowly until the achievement of critical mass when adoptions will accelerate. This phenomenon will generate a left skew in the adoptions/period curve. The Gamma-Shifted Gompertz (G-SG) model proposed by Bemmaor (1994) can capture both left and right skew and can also accommodate individual heterogeneity. In fitting the G-SG model, the left skew implied by the existence of a critical mass would be characterized by the parameter  $\alpha > 1$  (see p 221, Bemmaor and Lee, 2001).

Following Norton and Bass (1982, 1987), we set the G-SG model within a multi-national and multi-generational context. The cumulative density function,  $F_{get}$ , is specified by generation (ie. subscript,  $g$ ) and country (ie. subscript,  $c$ ).

This means that there is a skew parameter,  $\alpha_{gc}$ , associated with each country for each generation. Since we are concerned here with the causes of skewness, the other details of model formulation and estimation are given in Appendices A and B, respectively.

The estimation of the skew parameter was done in two ways; firstly each  $\alpha_{gc}$  is estimated individually for each country; secondly the skew was parameterized as a function of relevant covariates.

$$\alpha_{gc} = \exp \left( \beta_{0g} + \sum_{i=1}^k \beta_k X_{ic} \right). \quad (3)$$

The time subscript ( $t$ ) is dropped from (3) as all the covariates used (ie. membership of economic sector and geographical region, the cultural variable and lag introduction times) do not vary over time. These two estimations allow us to measure the proportion of the variation in country skew coefficients that can be captured by the covariates.

## 3 Description of Cellular Technology and Data Description

Analog cellular telephone technology was introduced in Europe and Japan in 1980 and in the US in 1983, by 2002 there were 1134 million mobile telephone connections worldwide. The second generation (2G) digital technology was introduced in 1993, allowing

the number of users per frequency to be increased by a factor of approximately three. The first generation (analog) bestows mobility to consumers in the developed countries and a means of communication in supply restricted fixed telephone networks in developing countries. In addition to better connections with increased privacy and less interference, the second generation digital systems allow text messages to be sent between mobile handsets.

Our data describes the number of connections to first generation analog and second generation digital cellular telephones covering the period from the introduction of each generation till 2002. The data cover 70 countries from six geographical regions and four economic sectors. For comparability across countries the data is scaled by population size to “cellular (analog / digital) ownership per 1000 people”.

## 4 Analysis

The analysis examines the effect of network externalities on the skew parameter of the G-SG model. We estimate a country based estimate first and then develop a covariate based estimate in parallel.

### 4.1 Skewness Estimation Using the G-SG Model

We might expect the diffusion of cellular telephones, especially in the first generation, to exhibit a left skew in countries where the fixed telephone networks are supply restricted. That is there is an unsatisfied demand for access to an inter-active network, which cellular telephones may satisfy. If the left skew exists, in the G-SG model, it will be manifested by the coefficient  $\alpha$  being greater than 1. Firstly, the skew coefficients were estimated for each country. It was found that the median of the analog skew coefficients varied more by economic sector than by geographic region;

for digital, the reverse was true. Box plots comparing analog skew by economic sector and digital skew by geographic region are shown in Figure 1. Left skew (indicated by  $\alpha > 1$ ) for analog adoptions is associated with lower middle and low income economic sectors, supporting the hypothesis that the network effects, predominant in these sectors, are delaying arrival at a critical mass. The mean skew coefficients for high and upper middle income countries are 0.74 (for both categories), 1.70 for lower middle income and 2.23 for low income countries. Similarly there is evidence of network effects in the diffusion of digital cellular but the mean skew coefficients are similar across economic regions. The mean for high income category is 1.54, upper middle income 1.37, lower middle income 1.44 and low income 1.35.

Secondly, the skew coefficient, parameterized as in (3), is re-estimated as a function of covariates. The covariate parameter estimates are summarized in Table 1. The skew estimates for analog are significantly affected by economic sector, attitude to risk and geographic region. Skew decreases with increased income and increases with the uncertainty avoidance index. Due to high colinearity between economic sector membership and waiting subscribers (as proportion of fixed telephone lines), we ran a separate regression of skew estimates with waiting subscribers. We found significant effect of waiting subscribers on skew estimates for analog phones.

The differences in economic sector and geographic region are less pronounced in the estimation of digital skew and attitude to risk is not significant. We need to keep in perspective that some of the differences in digital skew estimates can be due to sample size differences across different regions. The plot in Figure 2 compares the country skew estimate with the covariate based estimates. The x-axis represents 70 countries

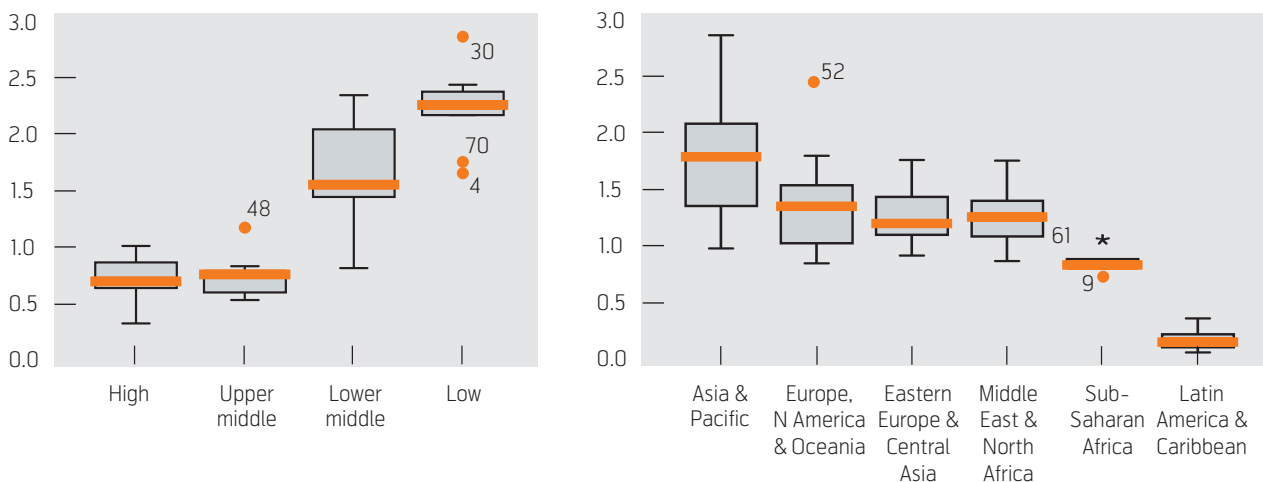


Figure 1 Box plots of Skew Estimates: Analog by Economic Sectors and Digital by Geographical Regions  
Key to outliers: 4 = Azerbaijan, 9 = Benin, 30 = Indonesia, 48 = Oman, 52 = Portugal, 70 = Vietnam, 61 = Tanzania

		Analog			Digital		
		Estimates	Std Error	P-value	Estimates	Std Error	P-value
	Intercept	1.112	0.203	0.000	0.847	0.195	0.000
Economic Variable	High Income <sup>1)</sup>	-1.674	0.119	0.000	0.161	0.146	0.267
	Upper Middle Income	-1.190	0.093	0.000	0.184	0.125	0.139
	Lower Middle Income	-0.403	0.081	0.000	0.273	0.116	0.018
Cultural Variable	Uncertainty Avoidance Index	0.010	0.002	0.000	0.087	0.111	0.433
Control Variables	Asia and Pacific	-0.239	0.071	0.001	-0.426	0.091	0.000
	Eastern Europe and Central Asia	-0.482	0.074	0.000	-0.034	0.088	0.697
	Middle East and North Africa	-0.134	0.061	0.027	-0.476	0.215	0.027
	Sub Saharan Africa	-0.118	0.081	0.146	-1.211	0.226	0.000
	Latin America and Caribbean	-0.534	0.087	0.000	-0.075	0.009	0.000
	Lag Introduction time	-0.046	0.004	0.000	0.001	0.002	0.580

<sup>1)</sup> Base categories for economic and geographical regions are Low Income category and European and North American countries respectively.

Table 1 Analog and digital skew estimates with covariates

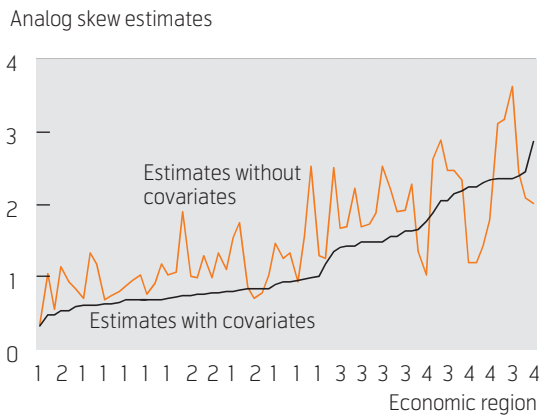


Figure 2 Plot of analog skew estimates with and without covariates

that belong to four economic regions (1 = High Income, 2 = Upper Middle Income, 3 = Lower Middle Income, and 4 = Low Income). The covariates explain 54 % of the variation of in country skew coefficients.

#### 4.2 Does Forecasting Performance of Model Improve if Skewness is Taken into Consideration?

Forecasts were computed for one to five year horizons, using data up to 1997 through to 2001. The results are summarized in Table 2 and Table 3.

In Table 2, the effect of the skew coefficient on forecasting is determined by comparing the forecasts of the multi-generation, international model with an estimated skew and with the skew coefficient constrained to be unity. For analog, the estimation of skew produces more accurate forecasts than constraining the skew parameter to unity. The covariate based skew produces more accurate forecasts than the country based skew, the increased accuracy persists for all horizons, whereas the accuracy of the country based skew forecasts deteriorates. For digital, there is no convincing evidence that the estimation of the skew parameter improves forecasting accuracy.

In order to judge the accuracy of a forecast, it is useful to have benchmark for comparison. In this case, fitting the Bass model to the number of cellular telephones adopted annually, country by country, is the benchmark chosen. This benchmark is reasonable in that it is a defensible approach if one cannot model the effect of different generations on adoption. In Table 3, the forecasts of the combined adoption of both generations are compared with those of the Bass model. The multi-generation, international model is less accurate on average for one year ahead forecasts than the Bass model. However, for a two year horizon they are equally accurate, for longer horizons the

Horizon in Years	1		2		3		4		5	
Generation – Analog, Digital	A	D	A	D	A	D	A	D	A	D
Geometric Mean (Country Skew/Skew = 1)	0.87	0.98	0.88	1.01	0.94	1.02	0.95	1.04	1.18	1.09
Geometric Mean (Covariate Skew/Skew = 1)	0.81	0.93	0.79	0.99	0.79	1.05	0.73	1.14	0.76	1.24

Table 2 Geometric mean of the ratio of root mean square errors for the country skew models and the covariate skew models with the root mean square of the model with the skew coefficient constrained to be 1

Bass is less accurate. The explanation for why the covariate skew model is less accurate than the country skew for longer horizons is that although the covariate based skew forecasts are more accurate for analog, they become poorer for digital (which dominates the later horizons).

## 5 Summary and Conclusions

The main question addressed is whether there is a left skew in the diffusion of analog or digital cellular telephones. The answer is that skewness exists for analog cellular telephones in lower middle and lower income countries. For digital there is some skewness, but it is less than for analog and does not vary significantly between economic sectors.

The accuracy of forecasting is improved if the left skew is included in the forecasting model for analog cellular telephones; for digital, the inclusion of skewness had little effect on accuracy. In a comparison with country based Bass models, forecast accuracy was improved by skewness for horizons greater than one year.

## References

Allen, D. 1988. New Telecommunications Services: Network Externalities and Critical Mass. *Telecommunications Policy*, 13, 255-264.

Baptista, R. 2000. Do Innovations Diffuse Faster within Geographical Clusters? *International Journal of Industrial Organization*, 18, 515-535.

Bass, F. 1969. A New Product Growth Model for Consumer Durables. *Management Science*, 15 (5), 215-227.

Bemmaor, A C. 1994). Modeling the Diffusion of New Durable Goods: Word-of-Mouth Effect Versus Consumer Heterogeneity. In: Laurent, G, Lilien, G L, Pras, B (eds.). *Research Traditions in Marketing*. Boston, MA, Kluwer, 201-213.

Bemmaor, A C, Lee, J. 2002. The Impact of Heterogeneity and Ill-Conditioning on Diffusion Model Parameter Estimates. *Marketing Science*, 21 (2), 209-220.

Craig, S, Susan, C, Douglas, P, Grein, A. 1992. Patterns of Convergence and Divergence among Industrialized Nations: 1960-1988. *Journal of International Business Studies*, 23, 773-787.

Dekimpe, M G, Parker, P M, Sarvary, M. 2000. Globalization: Modeling Technology Adoption tim-

Horizon in Years	1	2	3	4	5
Country Skew/Bass	1.16	0.99	0.86	0.83	0.63
Covariate Skew/Bass	1.10	0.99	0.90	0.92	0.81

Table 3 Geometric mean of the ratio of root mean square errors for the country skew models and the covariate skew models with the root mean square of the Bass model for combined analog and digital adoption

ing Across Countries. *Technological Forecasting and Social Change*, 63, 25-42.

Desiraju, R, Nair, H, Chintagunta, P. 2004. Diffusion of New Pharmaceutical Drugs in Developing and Developed Nations. *International Journal of Research in Marketing*, 21, 341-357.

Economides, N. 1991. Compatibility and the Creation of Shared Networks. In: Guerin-Calvert, M E, Wildman, S S (eds.). *Electronic Services Networks: A Business and Public Policy*. New York, Praeger Publishing Inc.

Everdingen, Y M, Waarts, E. 2003. The Effect of National Culture on the Adoption of Innovations. *Marketing Letters*, 14 (3), 217-232.

Ganesh, J, Kumar, V. 1996. Capturing the Cross-National Learning Effects: An Analysis of Cross-National of an Industrial Technology Diffusion. *Journal of Academy of Marketing Science*, 24 (Fall), 328-337.

Ganesh, J, Kumar, V, Subramanian, V. 1997. Learning Effects in Multinational Diffusion of consumer Durables: An Exploratory Investigation. *Journal of Academy of Marketing Science*, 25 (3), 214-228.

Gatignon, H, Eliasberg, J, Robertson, T S. 1989. Modeling Multinational Diffusion Patterns: An Efficient Methodology. *Marketing Science*, 8 (3), 231-247.

Granovetter, M. 1978. Threshold Models of Collective Behavior. *American Journal of Sociology*, 83, 1420-1443.

Gupta, S, Jain, D C, Sawhney, M S. 1999. Modeling the Evolution of Markets with Indirect Network Externalities: An Application to Digital Television. *Marketing Science*, 18 (3), 396-416.

Hagerstrand, T. 1967. *Innovation Diffusion as a Spatial Process*. Chicago, University of Chicago Press.

- Islam, T, Fiebig, D B. 2001. Modelling the development of supply-restricted telecommunications markets. *Journal of Forecasting*, 20, 249-264.
- Kalish, S, Mahajan, V, Muller, E. 1995. Waterfall and Sprinkler New Product Strategies in Competitive Global Markets. *International Journal of Research in Marketing*, 12, 105-119.
- Kumar, V, Ganesh, R, Echambadi, R. 1998. Cross-National Diffusion Research: What do We Know and How Certain are We? *Journal of Product Innovation Management*, 15, 255-268.
- Liebermann, Y, Paroush, J. 1982. Economic Aspects of Diffusion Models. *Journal of Economics and Business*, 34, 95-100.
- Lim, B-L, Choi, M, Park, M-C. 2003. The Late Take-off Phenomenon in the Diffusion of Telecommunications Services: Network Effect and Critical Mass. *Information Economics and Policy*, 15, 537-667.
- Madden, G, Coble-Neale, G, Dalzell, B. 2004. A dynamic Model of Mobile Telephony Subscription Incorporating a Network Effect. *Telecommunications Policy*, 28, 133-144.
- Mahler, A, Rogers, E M. 1999. The Diffusion of Interactive Communication Innovations and the Critical Mass: the Adoption of Telecommunications Services by German Banks. *Telecommunications Policy*, 23, 719-740.
- Norton, J A, Bass, F M. 1982. Evolution of Technological Generation: The Law of Capture. *Sloan Management Review*, Winter, 66-77.
- Norton, J A, Bass, F M. 1987. A Diffusion Theory Model of Adoption and Substitution for Successive Generations of High-Technology Products. *Management Science*, 33, 1069-1086.
- Putsis, W P, Balasubramanian, S, Kaplan, E H, Sen, S. 1997. Mixing Behavior in Cross Country Diffusion. *Marketing Science*, 16 (4), 354-369.
- Rogers, E M. 1995. *Diffusion of Innovations*, Fourth Edition. New York, The Free Press.
- Russell, T. 1980. Comments on the Relationship between Diffusion Rates, Experience Curves, and Demand Elasticities for Consumer Durable Technological Innovations. *Journal of Business*, 53 (3), 69-73.
- Schoder, D. 2000. Forecasting the Success of Telecommunications Services in the Presence of Network Effects. *Information Economics and Policy*, 12, 181-200.
- Steenkamp, J-B. E. M. (2001), "The Role of National Culture in International Marketing Research", *International Marketing Review*, 18(1), 30-44.
- Steenkamp, J-B E M, ter Hofstede, F, Wedel, M. 1999. A Cross-National Investigation into the Individual and National Cultural Antecedents of Consumer Innovativeness. *Journal of Marketing*, 63 (April), 55-69.
- Sundqvist, S, Frank, L, Puumalainen, K. 2005. The Effect of Country Characteristics, Cultural Similarity and Adoption Timing on the Diffusion of Wireless Communications. *Journal of Business Research*, 58, 107-110.
- Takada, H, Jain, D. 1991. Cross-National Analysis of Diffusion of Consumer Durable Goods in Pacific Rim Countries. *Journal of Marketing*, 55 (April), 48-54.
- Talukdar, D, Sudhir, K, Ainslie, A. 2002. Investigating New Product Diffusion across Products and Countries. *Marketing Science*, 21 (1), 97-114.
- Van den Bulte, C, Stremersch, S. 2004. Social Contagion and Income Heterogeneity in New Product Diffusion: A Meta Analytic Test. *Marketing Science*, 23 (4), 530-544.
- Yaveroglu, I S, Donthu, N. 2002. Cultural Influences on the Diffusion of New Products. *Journal of International Consumer Marketing*, 14 (4), 49-63.

## Appendix A – Estimation of the G-SG Extended to the Multinational Multi Generation Case

Within (2), we re-parameterize the model in Bass notation,  $b = p + q_i$  and  $a = q / p$ , where  $p$  is the coefficient of innovation and  $q$  is the coefficient of imitation. The Bass parameters are expressed as functions of the covariates as follows.

$$p_{get} = \exp \left( \beta_{(p)0g} + \sum_{i=1}^{k_p} \beta_{(p)i} Z_{(p)ic}(t) \right)$$

$$q_{get} = \beta_{(q)0g} + \sum_{i=1}^{k_q} \beta_{(q)i} Z_{(q)ic}(t)$$

If the cumulative number of adopters of generation  $g$  of the technology in country  $c$  at time  $t$  is  $Y_{get}$  then the observed new adoptions at time  $t$ ,  $y_{1ct} = Y_{1ct} - Y_{1ct-1}$  can be expressed as

$$y_{1ct} = m_{1ct} ((F_{1ct} - F_{1ct-1}) - (F_{1ct} F_{2c(t-\tau)} - F_{1ct-1} F_{2c(t-\tau-1)})) + \varepsilon_{1ct} \quad \sigma_{2ct}^2 = \{m_{2ct} P_{2ct}(1 - P_{2ct}) + m_{1ct} Q_{2ct}(1 - Q_{2ct})\}^\lambda \quad (11)$$

and

$$y_{2ct} = m_{2ct} (F_{2c(t-\tau)} - F_{2c(t-\tau-1)}) + m_{1ct} (F_{1ct} F_{2c(t-\tau)} - F_{1ct-1} F_{2c(t-\tau-1)}) + \varepsilon_{2ct}$$

where  $m_{gct} = \exp \left( \beta_{(m)0g} + \sum_{i=1}^{k_m} \beta_{(m)ig} Z_{(m)ic}(t) \right)$

We assume the errors are normally distributed,  $\varepsilon_{gct} \sim N(0, \sigma_{gct}^2)$ . The variance terms are given below.

$$\sigma_{1ct}^2 = \{m_{1ct}(P_{11ct}(1 - P_{11ct}) + P_{12ct}(1 - P_{12ct}))\}^\lambda \quad (10)$$

where  $P_{11ct} = (F_{1ct} - F_{1ct-1})$  and  $P_{12ct} = (F_{1ct} F_{2c(t-\tau)} - F_{1ct-1} F_{2c(t-\tau-1)})$  and

where

$$P_{2ct} = (F_{2c(t-\tau)} - F_{2c(t-\tau-1)}) \text{ and}$$

$$Q_{2ct} = (F_{1ct} F_{2c(t-\tau)} - F_{1ct-1} F_{2c(t-\tau-1)}) .$$

We estimate the model parameters by maximizing the (log) likelihood function:

$$\sum_g \sum_c \sum_t \ln \left( \phi \left( \frac{\varepsilon_{gct}}{\sigma_{gct}} \right) \right) \quad (12)$$

where  $\phi(\cdot)$  is the standard Normal density function, using the full information maximum likelihood (FIML) procedure.

## Appendix B – Estimates of G-SG – Coefficient of Innovations, Imitations and Market Potentials

Parameters	Gamma-Shifted Gompertz			
	Analog		Digital	
	Est. ( $\beta$ )	Std err.	Est. ( $\beta$ )	Std err.
<b>Coefficients of Innovation</b>				
Intercept	-5.6736**	0.4434	-3.5367	0.502
Newspaper per 10,000 people	-0.2884	0.2581		
TV per 10,000 people	-0.0114**	0.0024		
Patent Applications by Residents	0.0449**	0.0117		
Researchers in R&D as % of Labour Force	0.0466	0.1209		
Openness in Trade	0.4447**	0.0644		
Individualism Index	-0.731**	0.2111		
Uncertainty Avoidance Index	0.5979	0.3312		
Power Distance Index	-0.1536	0.1712		
Political Rights	-0.0617**	0.0169		
<b>Coefficients of imitation</b>				
Intercept	-0.0106	0.0748	-0.0400	0.2304
Main Telephones per 100 people	-0.0009*	0.0004	0.0013	0.0012
GDP per Capita	0.0155**	0.002	0.0014	0.0034
Mobility: Cars per 10,000 People	0.0018*	0.0008	0.0032*	0.0016
Gini Index	0.0022**	0.0007	0.0051*	0.0023
Nos. of Ethnic Groups	-0.0164*	0.0071	0.0015	0.0241
Female as % of Labor Force	0.0026**	0.0007	0.0024	0.0021
High-Low Cultural Context	-0.0030	0.0021	0.0037	0.0039
Lag Introduction / Intergeneration Time	0.0250*	0.0112	0.0334	0.0362
<b>Marketing effort</b>				
Connection Charge relative to GDP per Capita	0.1908	0.1982	-0.0976	0.0704
<b>(Incremental) Market Potential</b>				
Intercept	6.8949**	0.8230	6.5105**	0.3450
Connection Charge relative to GDP per Capita	-0.0180**	0.0025	-0.0286**	0.0063
High Income <sup>1)</sup>	-2.7004**	0.8365	2.3463**	0.2196
Upper Middle Income	-2.6237**	0.7220	1.8995	0.1966
Lower Middle Income	-0.9252	0.5440	1.1368	0.1745
GDP Growth Rates	0.0181**	0.0054	0.0443	0.0100
Gini Index	0.0253**	0.0044	-0.013	0.0052
Economic Risk <sup>2)</sup>	-0.0120	0.0063	-0.0504	0.0085

\*\*p < 0.01; \*p < 0.05; <sup>1)</sup> Binary coded base: low Income Group; <sup>2)</sup> higher risk rates is less risky

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*Professor Nigel Meade is an experienced statistical modeler with a background in operational research and statistics applied to innovation diffusion and finance. He is associate editor of the International Journal of Forecasting and the European Journal of Finance. He has published over 50 papers and 8 book chapters and successfully supervised more than 20 PhD students.*

*n.meade@imperial.ac.uk*

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*Dr. Towhidul Islam is an Associate Professor of Marketing, University of Guelph, Canada. His PhD is in Management Science from Imperial College, University of London, UK. He has held research and faculty positions at the University of Sydney, Australia, University of Technology, Sydney, Australia, Dalhousie University, Canada, and University of Northern BC, Canada. His main research interests are in consumer science and new products diffusion, especially in areas of application of statistical and econometric methods to further understanding of consumer behavior and improve marketing decision making. His work has appeared in the Journal of Consumer Research, Management Science, International Journal of Research in Marketing, the Journal of Business Research, the International Journal of Forecasting, the Journal of Forecasting, and the European Journal of Operational Research, among other outlets.*

*islam@uoguelph.ca*