ARTICLE IN PRESS

International Journal of Forecasting ▮ (▮▮▮▮) ▮▮▮–▮▮▮

Contents lists available at ScienceDirect

International Journal of Forecasting

journal homepage: www.elsevier.com/locate/ijforecast

The diffusion of mobile social networking: Exploring adoption externalities in four G7 countries

Miriam Scaglione[a], Emanuele Giovannetti[b,c], Mohsen Hamoudia[d,*]

[a] University of Applied Sciences and Arts Western Switzerland Valais, School of Management and Tourism, Switzerland
[b] Institute for International Management Practice, Anglia Ruskin University, UK
[c] DSE University of Verona, Italy
[d] Orange – France Telecom Group, France

ARTICLE INFO

Keywords:
Social networking
Diffusion models and innovation
Bass model
Heterogeneity of adoption
Gamma/shifted Gompertz model
ICT and social forecasting

ABSTRACT

The diffusion of Mobile Social Networking (MSN) is driven by the development of new devices and improved mobile broadband. The instantaneous nature of MSN exchanges enhances the value of data access for mobile users, which generates network externalities. We explore the presence of these externalities in the diffusion of MSN in France, the UK, the US and Germany. For these countries, we compare estimates of two diffusion models: the Bass model and the Bemmaor model. We find evidence of network externalities in MSN adoption for all of these countries, captured by the *left skew* of the cumulative adoption curves. This evidence is confirmed even after taking into account the contrasting effect of heterogeneity in the propensity to adopt. Our results provide content providers, operators and regulators with insights about marketing strategies, helping with policy formulation under the combined presence of network externalities and heterogeneity.

1. Introduction

Over the last thirty years, the telecommunications industry has grown in both size and complexity, due mostly to the sector convergence of different applications, market deregulation and the penetration of the Internet. Prior to these transformations, the value chain of telecommunications providers (telcos) was characterised by a supply chain that was articulated into the sequence of: procurement, network operations, network-related service provisioning, billing, and added-value services and sales. Since 2007, however, the profitability associated with voice services has declined dramatically (West & Mace, 2010). Moreover, newcomers, defined as "over the top" companies (OTT), have progressively taken advantage of the standard IP-based Internet connection by adding new services. Accordingly, infrastructure and services have progressively become independent (Grove & Baumann, 2012, p. 40). One such example is Skype, which was able to lower call rates by combining Internet IP telephony with traditional telephony and reaping the associated economies of scale. Despite renewed efforts by telcos to provide IPTV and TV via telephone lines, OTT services (e.g., YouTube or Netflix) have emerged as more successful.[1]

These sector changes mean that telcos' products are progressively losing value by being commoditised (Funk,

* Corresponding author.
E-mail address: mohsen.hamoudia@orange.fr (M. Hamoudia).

[1] Moreover, the telcos' development of Internet-based applications has been slower in Western countries than in the Far Eastern ones. Funk (2007) identified the main causes of this as being related to differences in both the underlying architecture and priorities, with western companies focussing mainly on business users.

http://dx.doi.org/10.1016/j.ijforecast.2015.03.005
0169-2070/

2011; Grove & Baumann, 2012; West & Mace, 2010). The future and the modalities of telcos' market evolution depend critically on these developments. A key driver of this evolution is found in the fact that OTT services have increased the value of mobility for web-based services significantly. This is due mainly to the explosion of services based on user-generated content that allow real-time information sharing. West and Mace (2010) grouped these OTT services into five main categories:

- *additional communication features* that supplement or replace voice calling, i.e. SMS, e-mail, videoconferencing;
- *additional computing features* for third-party software vendors, such as add-on software packages, e.g., games or business productivity;
- *commercial content*, such as multimedia news and information services, movies, music and ringtones;
- *user-generated content*, typically photo and video sharing, blogging, wikis and social networking such as Facebook and Twitter; and
- *e-commerce* applications, allowing online commercial transactions either through dedicated client software or just through a browser. Typical commercial applications include online banking, auction sites like eBay, and accommodation and air travel booking systems such as Booking.com and TripAdvisor.

The diffusion of these services has increased the demand for mobile multimedia data significantly, and their evolution provides important insights into telcos' market infrastructure requirements and revenue forecasts.

Mobile Social Networking (MSN) is an essential data service that is currently showing strong growth. Recent estimates claim that there will be 2.4 billion MSN users by the end of 2016, compared to the 948 million active ones by end of 2012 (Informa, 2012). MSN diffusion is driven by the development of new devices, smartphones and tablets, improved mobile broadband and 3G and 4G/LTE networks, allowing quick access to the Internet, competitive pricing, and the proliferation of web content. MSN subscribers have instantaneous access to multiple sources of information when they are on the move, with the possibility to contribute. This implies that, for every MSN user, the amount and relevance of information available increases with the level of MSN diffusion among her/his peers. Hence, higher levels of MSN penetration increase the expected utility of both existing and prospective mobile users.

This increasing incentive to adopt, due to the increasing number of existing adopters, characterises markets with network externalities. Our research objective is to assess the potential presence of network externalities and to investigate their role in shaping the process of adoption and diffusion of MSN in four different countries: Germany, France, the UK and the US.

The remainder of the paper is structured as follows. After this introduction, Section 2 provides a literature review. Section 3 introduces the relevant models that are used later in the econometric analysis of the diffusion processes. Section 4 briefly describes the data sources, while Section 5 presents the diffusion model specifications, the forecasting methodology we use in this study, and the main results. Finally, Section 6 concludes the paper and indicates areas for future research.

2. Literature review

Social Networking (SN) sites are "web-based" services "that allow individuals to construct a public or semi-public profile within a bounded system; articulate a list of other users with whom they share a connection and view and traverse their list of connections and those made by others within the system" (Boyd & Ellison, 2007, p. 211). The role of SNs goes beyond the spread of personal information, because they also provide information about public affairs, by allowing citizens to express and broadcast opinions within online communities. In the 2008 US Presidential Election, nearly 10% of persons aged under 30 years signed up to candidates' sites, not only gaining instant campaign information but also posting and sharing comments online (Kim, 2011).

The identifying nature of SNs is to be found in the interaction between peers. Hence, the number of present adopters influences the future decisions of those who have not yet adopted and shapes aggregate diffusion patterns. Innovations based on users' interactions in SNs, and in telecommunications more generally, typically exhibit network externalities, as they become more valuable to their users as the number of adopters increases (cf. Mahler & Rogers, 1999, p. 720).

The economic literature has identified two main types of network externalities – direct and indirect – depending on whether the benefits of adoption are perceived by the users of a given service or commodity, or by those using other complementary products and services. Specifically, Katz and Shapiro (1985, 1986) define *direct network externalities* as those characteristics that increase the utility of a good or service as the number of users increases (e.g., mobile phone and e-mail). One key feature of these network externalities is that the increase in utility induced from present adopters also influences future adoption patterns, as present adoption levels affect expectations about the future utility of adoption (cf. Rogers, 2003, p. 315). *Indirect network externalities*, on the other hand, arise when the utility of a good or service increases with the number of users of a complementary product (e.g. the utility for a consumer of a DVD player increases with the increased penetration of DVD titles). In particular, for hardware and software products, the utility of the former depends of the number of compatible applications of the latter (Peres, Muller, & Mahajan, 2010; Stremersch, Tellis, Franses, & Binken, 2007). The presence of network externalities often implies the need for a *critical mass* of adopters in order for the diffusion of an innovation to succeed, as a "critical mass occurs at the point at which enough individuals have adopted the innovation so that the innovation's further rate of adoption becomes self-sustainable" (Rogers, 2003, p. 313).

Arthur (1989) and David (1985) provided pioneering contributions to the study of the effects of network externalities on the dynamic processes of the diffusion of innovations. They focused on the non-linear and path-dependent nature of these diffusion processes due to the presence of positive feedback, which causes adoption to become self-reinforcing only after reaching a critical threshold. Giovannetti (2000, 2013) identified the micro-economic conditions under which the opposite effects

Please cite this article in press as: Scaglione, M., et al., The diffusion of mobile social networking: Exploring adoption externalities in four G7 countries. International Journal of Forecasting (2015), http://dx.doi.org/10.1016/j.ijforecast.2015.03.005

arise, i.e. when the adoption of an innovation by neighboring competitors prevents a firm from adopting the same technology. Under these conditions, adoption is partial at any point in time because of negative adoption externalities, without assuming a priori differences between innovators and imitators or in the individual propensity to imitate.

Allen (1988) pointed out that the notion of critical mass applies only to new telecommunication services, not to existing ones[2] (see also Mahler & Rogers, 1999). However, the connection of mobile phones to other services, such as music, video, broadcasting and payments, means that the critical mass in the adoption of a new device is related to previously reached critical masses in these services, and vice versa (see Funk, 2011).

3. Two models for capturing the role of network externalities in the diffusion of MSN

The main objective of this paper is to analyze MSN diffusion across four G7 countries and to assess the potential role played by network externalities in these countries' MSN diffusion patterns.

Our starting point is the seminal Bass model of diffusion (Bass, 1969), an extension of Rogers' (1962) ideas on the diffusion of innovations, quantifying the factors that drive the individual and organizational adoption of new products.

Eq. (1) shows the Bass function for the diffusion of a new product, where $N(t)$ is the cumulative number of adopters at time t, m is the eventual level of market adoption, the *ceiling*, and the parameters p and q are the coefficients of *innovation* and *imitation* respectively:

$$\frac{dN(t)}{dt} = \underbrace{p(m - N(t))}_{\text{Adoption due to external influence or independent adoption}} + \underbrace{\frac{q}{m}N(t)(m - N(t))}_{\text{Adoption due to internal influence or internal adoption}}. \quad (1)$$

The *innovation* coefficient p captures the propensity to adopt the new product that is driven by external information. On the other hand, the *imitation* coefficient q represents the propensity to adopt it that is due to interpersonal communication channels (Mahajan, Muller, & Srivastava, 1990). Eq. (1) also contains and generalizes two extreme cases (see Meade & Islam, 2006): a *pure innovation* one, reducing to a modified exponential function, when $q = 0$ and $p > 0$, and a *pure imitation* one when $p = 0$ and $q > 0$. In this last case, the Bass equation reduces to a logistic diffusion curve, reproducing the pioneering contribution by Mansfield (1961) on the diffusion of innovations.

The parameters q and p jointly determine both the shape and the scale of a diffusion curve resulting from the differential equation given in Eq. (1). In particular, the sum of these parameters, $p + q$, controls the scale of both the cumulative adoption curve and the instantaneous adoption curve, while their ratio, q/p, defines the shapes of these curves. In particular, the greater the q/p ratio, the more prominent the S-shape, and the more *left-skewed* the cumulative adoption curve, leading to a slower penetration rate (see Bemmaor & Lee, 2002; Meade & Islam, 2006). Hence, a systematic comparison of the *innovation* and *imitation* parameters, p and q, may provide essential information for the estimation and forecasting of the adoption of new products across countries, as well as for that of different innovations within the same country.

The Bass model is usually described by bell-shaped instantaneous adoption curves. These curves have three important values that identify different categories of adopters. The initial value of relevance is the first inflexion point, T1, which separates *early adopters* from the *early majority*. The second crucial value is the peak of absolute adoptions T*, which identifies and discriminates between the *early majority* and the *late majority*. Finally, the last crucial value of the distribution is given by the second inflexion point, T2, separating the *late majority* from the *laggards* (Mahajan et al., 1990, pp. 42–43, Figs. 3 and 4).

The original Bass model assumes that the diffusion is taking place within a homogeneous and fully connected social system. In this framework, the probability that an individual adopts an innovation is linear with respect to the number of previous adopters, after considering other external factors, such as advertising (Bass, 1969, and Mahajan & Muller, 1979). However, this approach to diffusion seems to overemphasize the influence of word-of-mouth communication without capturing the role of consumer heterogeneity (Peres et al., 2010). Allen pointed out that the perception of critical mass could "vary between individuals" (Allen, 1988, p. 260), raising the need to address heterogeneity when modelling the individual disposition toward adoption.

Within the Bass framework, the heterogeneity in the propensity to adopt can be analyzed by a comparative study of the diffusion of a product or service across different populations. Along these lines, Van den Bulte and Stremersch's (2004) study of the diffusion of 52 consumer durables across 28 countries found that the shape of the adoption curve may be affected by national cultural differences and income inequality across countries. Similarly, Islam (2014) captured heterogeneity in the adoption of renewable energy using individual-level data.

Bemmaor (1994), on the other hand, proposes a general diffusion model that explicitly introduces heterogeneity in the individual propensity for adoption. This model assumes that individual-level times for adoption (or first purchase) vary following a shifted Gompertz distribution function (Bemmaor, 1994, p. 204):

$$f(t|\eta) = be^{-bt}\exp\left\{-\eta e^{-bt}\right\}[1 + \eta(1 - e^{-bt})], \quad t > 0 \quad (2)$$

where b is the scale parameter and

η is the shape parameter.

[2] For example, the adoption of cellular telephony (2G) across 36 countries shows a higher likelihood of critical mass only in pioneering markets (Grajek & Kretschmer, 2012). Also, the network externalities in the diffusion of analogue cellular phones were higher than for digital phones for lower and lower-middle income countries (Meade & Islam, 2008).

In Eq. (2), the scale parameter b is the same across adopters, while the shape parameter η, which captures the heterogeneity in the individual-level propensity to adopt, varies across adopters.[3]

Bemmaor (1994, p. 204) also shows that heterogeneous individual-level propensities to adopt may still produce an aggregate behavior that is equivalent to that captured by the Bass model. This is possible when the individual heterogeneity parameter η follows the exponential distribution function[4] $k(\eta)$:

$$k(\eta|\beta) = (1/\beta)e^{-(1/\beta)\eta}, \quad \beta > 0. \tag{3}$$

To allow for more heterogeneity in individual-level adoption propensities, Bemmaor proposes a different model whereby the individual heterogeneity parameter, η, is assumed to be drawn from a Gamma distribution, with shape parameter α and scale parameter β. Bemmaor shows that individuals' homogeneity, in their propensity to adopt, is related directly to the distribution shape parameter α.[5] When α tends to infinity, the population is homogeneous, so that the propensity to adopt is the same across potential adopters, irrespective of the individual adoption time. When α equals one, the Gamma distribution reduces to the exponential distribution. That is, in this specific case, the Bemmaor model is equivalent to the Bass model. When α is close to zero, heterogeneity is at a maximum, and potential adopter acceptance rates differ across the population (Bemmaor, 1994, p. 220).

The resulting Gamma/Shifted Gompertz (G/SG) aggregate cumulative distribution function has the closed-form expression:

$$F(t) = [1 - e^{-bt}]/[1 + \beta e^{-bt}]^{\alpha}. \tag{4}$$

In Eq. (4), the parameters b and β can also be expressed in terms of the Bass model parameters, using the facts that $b = p + q$ and $\beta = q/p$. For fixed values of b and β, the shape parameter of Eq. (4), α, measures the adopters' population heterogeneity and provides crucial information about the "extra Bass" effect on diffusion, capturing the shape effect that is due to the population heterogeneity rather than to the ratio of adopters to innovators, as is emphasized by the q/p ratio in the Bass model. This parameter, α, in affecting the skew of the cumulative adoptions curve, also helps to assess the evidence for the presence of network externalities in adoption choices. These externalities are manifested when the shape is *left skewed*, as usually happens for interactive innovations (Mahler & Rogers, 1999; Meade & Islam, 2008).

The G/SG model in Eq. (4) is of particular interest, as it generates diffusion curves that are compatible with additional *skew* compared to the Bass ones, either to the left or to the right, depending on the value of α. This extra *skew* captures the role of heterogeneity, for given levels of p and q. The skew parameter α also accounts for the potential model's bias by considering "the *skew* embedded in more flexible diffusion models, i.e., G/SG, than the Bass model labeled as 'extra-Bass'" (Bemmaor & Lee, 2002, p. 210).

A significant relationship links the shape parameter α in Eq. (4) with the scale and shape parameters in the Bass model of Eq. (1). If $\alpha \approx 0$, then the shape of Eq. (4) is close to an exponential curve equivalent to the one arising in the Bass model when there are no imitators, $q = 0$. As α tends to infinity, the G/SG curve resembles a logistic curve. These findings have interesting managerial implications, as the diffusion of an innovation will need to rely on a high degree of individual heterogeneity in the case of $\alpha \approx 0$ (Bemmaor & Lee, 2002).

The G/SG Bemmaor diffusion model captures the heterogeneity of adoption propensities across individuals, without identifying its sources. In this framework, Chatterjee and Eliashberg (1990) claim that "aggregation across individuals yields the penetration curve; (but) the distribution of individual adoption times determines the rate and pattern of adoption" (p. 1058). These, possibly multiple, interpretations have been captured well by Van den Bulte and Stremersch (2004), who state that "(…) it is impossible to unambiguously interpret the model parameters of any single diffusion curve as reflecting social contagion or heterogeneity in the propensity to adopt" (p. 530).

In addition to ignoring heterogeneous adoption propensities among the population, the Bass model, as expressed by Eq. (1), also ignores the possible role of a critical threshold that is necessary in order for an individual to adopt (Van den Bulte & Stremersch, 2004). Bartels and Islam (2002) and Islam and Fiebig (2001) provide an alternative explanation for the presence of a *skew* in the diffusion of innovations in the telecommunications market, showing that this *skew* may arise due to supply restrictions. Van den Bulte (2002) performs a meta-analysis of different innovations across countries, showing how both a high imitation propensity q and a low innovation one p may indicate the presence of network externalities, as adopters may wait to see whether a critical mass has been achieved before adopting, particularly for risky technologies or when there are competing standards. A qualitative study of German banks has also shown that, relative to non-interactive innovations, the diffusion of interactive innovations (such as electronic funds transfers and home banking for private customers) was slow until critical mass was reached (Mahler & Rogers, 1999). In this case, the S-shape for non-interactive innovations should be less pronounced, more *right skewed*, having a smaller q/p ratio than that for interactive innovations, which are more *left skewed*. Bauckhage, Kersting, and Rastegarpanah (2014) also use the Bass and G/SG models jointly for comparing

[3] The lower η is, the higher the individual propensity to adopt and the lower the expected time of adoption. If η tends to 0, then the individual-level times for adoption tend to an exponential distribution.

[4] This shape assumption has some important consequences. Firstly, with the coefficient of variation of an exponential density at unity, the degree of heterogeneity in the Bass model is constrained a priori; consequently, it "leads to a faster diffusion than expected when the population is more homogeneous than the model assumes" (Bemmaor, 1994, p. 216). Secondly, given that the mode of the exponential distribution is zero, the Bass model assumes that consumers are more likely to buy at the launch date, which is questionable (Bemmaor, 1994; Bemmaor & Lee, 2002).

[5] The parameter α plays a crucial role in shaping the gamma distribution, and $\alpha^{-1/2}$ is the Gamma distribution coefficient of variation (standard deviation $= \beta\alpha^{1/2}$ over the mean $\beta\alpha$).

the collective interest in social media services, and find that it follows clear diffusion patterns across different languages and regions.

In our model, we will interpret the possible emergence of a *left skew* as originating from network externalities on the demand side. These are captured via a combined analysis of the skew and shape parameters of the estimated Bemmaor and Bass models. Indeed, the shape parameters, $\beta = q/p$, provide insights about the existence of a *critical mass* when comparing diffusion across countries or comparing different innovations across the same population, while the *skew* parameter of the Bemmaor model, α, identifies the presence of an "extra-Bass" skew for given values of the shape parameter $\beta = q/p$.

In the following sections, after describing the data, we will start by investigating the differences in the patterns of MSN adoptions across four G7 countries,[6] by estimating the Bass parameters of innovation, p, and imitation, q, together with their ratio, q/p (see Stremersch, Muller, & Peres, 2010; Stremersch et al., 2007). We will then investigate the existence and role of network externalities for these diffusion processes using the Gamma/Shifted Gompertz curve approach (Bemmaor, 1994; Bemmaor & Lee, 2002), with a specific focus on the role played by the *skew* parameter α (Meade & Islam, 2008).

4. Data

The data set utilized in our estimates consists of four monthly series of the numbers of active and unique MSN users from April 2007 to October 2012 (source: comScore Mobilens 2012, Fig. 1). Active users are individuals who are registered with at least one MSN or community service such as Facebook or LinkedIn and log in to this at least once a month via their mobile phone, mainly via smartphone. This is not the same as the number of registrations to social networks, because many subscribers will not access these services via their mobile phones. Therefore, the number of unique and active MSN users will always be smaller than the total number of registrations for these services. We have based our estimates on the raw monthly data, without any adjustments for seasonality.

5. Methodology and results

5.1. Modelling and accuracy evaluation

In this section, we introduce the estimates for two alternative diffusion model specifications, namely those of Bass and Bemmaor, using data on MSN adoptions in the US, the UK, France and Germany. Following Srinivasan and Mason (1986), the parameters of the Bass model, presented in Eq. (1), were estimated by taking period adoptions to be the difference between two subsequent cumulative

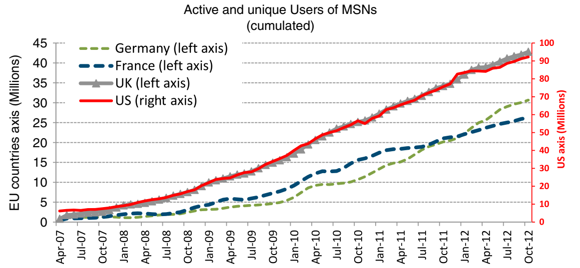

Fig. 1. Mobile social networking (MSN) for France, the UK and Germany (left axis), and the US (right axis).

distribution functions, multiplied by the eventual market size. The parameters of the Bemmaor model, presented in Eq. (4), were obtained by focusing on total adoptions, estimated through the relevant cumulated adoptions function, again multiplied by the eventual market size (Peers, 2011).[7]

In more detail, to estimate the Bass model, let $X_{j,t}$ be the number of MSN adoptions in period t for country j. These values $X_{j,t}$ are calculated as the difference between two consecutive monthly observations of cumulated MSN adoptions:

$$X_{j,t} = N_{j,t} - N_{j,t-1}.$$

Srinivasan and Mason's (1986) method is based on the idea that the increment in MSN penetration at time t in country j is given by the eventual market size m, multiplied by the difference between the cumulated distribution functions at two subsequent time periods: $F_{j,}(t) - F_{j,}(t-1)$, where $F_j(t) = \left[\frac{1-e^{-bt}}{(1+\beta e^{-bt})}\right]$ is the closed form solution of the Bass differential equation in Eq. (1).

Hence, the parameters for the Bass model specifications, reported in Table 1, are obtained using a *nonlinear least squares* estimation of the equation:

$$\begin{aligned} Xj(t) &= m\left(F_j(t) - F_j(t-1)\right) + \varepsilon_{j,t} \\ &= m\left\{\left(\frac{1-e^{-bt}}{(1+\beta e^{-bt})}\right) - \left(\frac{1-e^{-b(t-1)}}{(1+\beta e^{-b(t-1)})}\right)\right\} \\ &\quad + \varepsilon_{j,t}. \end{aligned} \tag{5}$$

The estimates for the Bemmaor models, on the other hand, were obtained through a procedure focussing on the cumulative number of adoptions for each country j at time t, $N_j(t)$. Bemmaor and Lee (2002) show that the cumulative distribution function for the G/SG model is given by Eq. (4) discussed above: $F_j(t) = \left[\frac{1-e^{-bt}}{(1+\beta e^{-bt})^{\alpha}}\right]$.

Hence, for each country, the relevant parameters for the G/SG Bemmaor models reported in Table 1 are obtained by estimating Eq. (6) using *nonlinear least squares*, where the equation is obtained by multiplying the eventual market

[6] Islam and Meade (2012), when studying multi-country diffusion, suggested estimating these models by pooling the data to capture any cross-country heterogeneity. While this step is essential when the time series available are not sufficiently long, the length of our data set allows us to focus on separate estimates.

[7] While it would be preferable to estimate the two models using only one procedure, the present choice was dictated by the non-convergence of the estimates for the Bemmaor G/SG model when using Srinivasan and Mason's (1986) method. The authors thank Prof Bemmaor for his advice on the estimation procedure.

Table 1
Bass and Bemmaor model estimations for Germany, the US, the UK and France. Estimation period: April 2007 to October 2012.

Country	Unique users of mobile phones by 2017[a]	Model	Eventual market (m)	Eventua l market/ population	p	q	alpha	$beta = q/p$	$b = p + q$	R2-adj	Root MSE	AIC
GE	73 580 000	Bass	45,353,834 (8,274,894)	0.6164	0.00091 (0.0003)	0.07582 (0.0148)	1	83.6268 (51.3703)	0.076729 (0.0145)	99.91	286 954	1668.854
		Bemmaor	43,702,722 (4,832,431)	0.5939	0.00013 (0.0001)	0.10323 (0.0194)	0.57284 (0.1117)	822.7707 (962.7)	0.103352 (0.0193)	99.7	517 300	1774.955
FR	54 878 000	Bass	30,786,488 (3,759,263)	0.561	0.00309 (0.0011)	0.0698 (0.014)	1	22.62485 (11.8859)	0.072883 (0.0135)	99.9	269 717	1660.677
		Bemmaor	29,657,525 (1,545,432)	0.5404	0.00317 (0.00218)	0.0723 (0.0151)	1.03025 (0.2993)	22.78496 (20.3374)	0.075468 (0.013)	99.6	575 276	1789.189
UK	57 409 000	Bass	56,211,699 (5,450,854)	0.9791	0.00457 (0.0001)	0.04935 (0.0081)	1	10.80151 (3.0630)	0.05392 (0.0076)	100	240 021	1645.28
		Bemmaor	53,515,230 (2,626,945)	0.9322	0.00209 (0.0008)	0.06419 (0.0095)	0.69317 (0.0994)	30.6881 (16.8237)	0.06628 (0.0087)	99.9	476 414	1763.922
US	233 807 999	Bass	104,820,000 (13,440,497)	0.4483	0.00376 (0.0012)	0.06346 (0.0115)	1	16.86079 (8.5984)	0.067228 (0.0130)	99.9	896 973	1819.295
		Bemmaor	103,590,000 (4,090,815)	0.4431	0.00072 (0.0004)	0.09057 (0.0125)	0.48973 (0.0671)	125.6457 (86.5332)	0.091294 (0.0087)	99.66	1 673 266	1932.259

R2-adj is in percentages.
[a] Source: GSMA Intelligence (2012).

size parameter, m, by the G/SG cumulative distribution function:[8]

$$N_j(t) = mF_j(t) + \varepsilon_{j,t} = m\left[\frac{1-e^{-bt}}{\left(1+\beta e^{-bt}\right)^{\alpha}}\right] + \varepsilon_{j,t}. \quad (6)$$

As was discussed earlier, the relationships $q = \beta \times b/(\beta + 1)$ and $p = b/(\beta + 1)$ allow the Bass model parameters p and q to be derived from the Bemmaor model parameters β and b. These relations will be used to facilitate the comparisons of the findings of the two models.

To evaluate and compare the accuracies of the different models, we used a cross-validation procedure based on a rolling forecasting origin, as this allows for multi-step errors (see Hyndman & Athanasopoulos, 2014, section 2/5, Evaluating forecast accuracy subsection: Cross-validation). The first out-of-sample data, or testing sample, begins at observation 33 (Dec. 2009), and the maximum number of steps ahead that we test is 18 months. For each rolling origin, the model's parameters were recalculated before being used for the generation of the L-step forecasts.[9]

The measure adopted for assessing the forecasting accuracy is the absolute percentage error, *ape*. For each country, model and rolling training sample set, where the last observation period is set at T, the L-step error forecast is defined as:

$$ape_{T+L} = 100\left|\frac{y_{T+L} - \hat{y}_{T+L}}{y_{T+L}}\right| \quad \text{where } T = 1, \ldots, 67 - L.$$

The global evaluation of the different models was then based on both the medians and the geometric means of the *apes calculated* for each L-step-ahead value, based on the different origins of the out-of-sample test.

In order to improve and judge the accuracy of our alternative estimation models, two additional models were also estimated:

- the random walk with drift L-step forecast (Islam, Fiebig, & Meade, 2002):

  $\hat{y}_{T+L} = y_T + L\hat{\theta}_0,$

  where the naïve trend is:

  $$\hat{\theta}_0 = \frac{1}{T-1}\sum_{i=2}^{T}(y_i - y_{i-1}); \quad \text{and}$$

- a drift estimated over seasonal differences:

  $$\hat{\theta}_0 = \frac{1}{T-12}\sum_{i=13}^{T}(y_i - y_{i-12}).$$

5.2. Results

Table 1 reports the estimates for both the Bass and Bemmaor models for the adoption (number of active and unique users) of MSN for three European countries (France, United Kingdom and Germany) and the United States. Overall, the values of adjusted R^2 are high. For each country, the Bemmaor model adjusted R^2 values are marginally smaller than the Bass ones, and the root mean square errors for the Bemmaor models are roughly twice as large as those for the corresponding Bass ones. The Akaike Information Criterion (AIC) values are also in line with these findings: the AICs for the Bass models are smaller than those associated with the Bemmaor ones for all countries.[10]

The analysis of the shape parameters is essential to an understanding of the dynamics of MSN diffusion and the presence of network effects. For the UK, the shape parameter $\beta = q/p$ estimated for the Bass model ($\beta = 10.8$) is lower than that estimated for the Bemmaor model ($\beta = 30.7$). Germany and the US also have smaller estimates for their shape parameters β when they are estimated using the Bass model than when they are estimated using the Bemmaor model.

The estimation of the *skew parameter*, α, in the G/SG Bemmaor model, based on Eq. (6), is introduced in order to capture the presence of externalities, in conjunction with the shape parameter, β, while taking into account the impact of heterogeneity on the diffusion skew.

Our estimates, reported in Table 1, show that France's *skew* parameter α is close to unity. Moreover, the estimates of p and q for the two models, Bemmaor and Bass, are similar for the French data; the same is true for the scale (b) and shape (β) parameters. This result is of particular interest because the Bemmaor and Bass models are the same when α equals one.

Finally, the size of the estimate of the eventual market (the *ceiling m*) also shows an interesting pattern. In every country, the eventual market m estimated using the Bemmaor model is smaller than that estimated using the Bass one.

5.3. Model accuracy evaluation

Table 2 shows the evaluation of the rolling forecast grouped by L, the number of steps ahead we are forecasting ($L = 1 \ldots 18$).

From the data, one can see that the global accuracy levels of the two naïve models are both lower than those of the Bass and Bemmaor ones; this is especially true for the seasonal naïve model. For the trend naïve model, the one-step-ahead forecasts are similar to those of the Bass and Bemmaor models, but the accuracy decreases rapidly for longer horizons.

Using simulated data, Bemmaor and Lee (2002) showed that the Bemmaor model outperforms the Bass model for one-step-ahead forecasts, when considering the mean of

8 This estimation procedure is discussed in detail by Peers (2011).

9 A customized program embedded in the Proc model (macro programming) was used to conduct the analysis, together with the SQL language and Proc univariate. This program also generated the files for each origin and step in SAS Institute V9.3.

10 This apparently poorer performance of the Bemmaor models in fitting the sample data could be due to the different estimation algorithms used, as was discussed above.

Please cite this article in press as: Scaglione, M., et al., The diffusion of mobile social networking: Exploring adoption externalities in four G7 countries. International Journal of Forecasting (2015), http://dx.doi.org/10.1016/j.ijforecast.2015.03.005

Table 2
Forecasting accuracy levels of our two models (Bass and Bemmaor) and of two deterministic trend models based on the naïve trend and on a Drift on seasonal differences seasonality for the four countries.

L-step-ahead (sample size)	US						France					
					Det. trend						Det. trend	
	Bass		Bemmaor		Naive on trend	Drift seas. diff.	Bass		Bemmaor		Naive on trend	Drift seas. diff.
	Median	Geo. Mean	Median	Geo. Mean	Median	Median	Median	Geo. Mean	Median	Geo. Mean	Median	Median
1(34)	0.89	0.63	1.85	1.76	0.72	14.62	1.22	1.21	3.20	2.73	1.20	14.28
2(33)	1.64	1.20	2.19	2.21	3.59	3.90	2.41	2.44	4.11	3.65	3.75	4.16
3(32)	2.91	2.13	3.33	2.63	6.76	2.46	3.44	3.14	4.89	4.41	6.06	2.35
4(31)	2.59	2.99	4.50	3.32	9.08	5.36	4.66	4.76	5.94	4.95	9.05	5.26
5(30)	4.25	3.57	5.69	4.16	11.36	8.41	6.07	4.69	6.43	5.28	11.42	8.43
6(29)	4.66	3.99	5.96	4.43	13.34	10.90	6.47	7.30	6.99	5.74	12.61	10.22
7(28)	4.99	4.27	5.95	5.46	15.48	13.48	7.95	8.28	7.65	7.21	14.64	12.60
8(27)	5.82	5.15	5.70	6.45	19.14	17.45	8.93	9.10	**7.82**	**7.45**	16.39	14.70
9(26)	7.99	5.98	5.48	8.09	21.07	19.56	9.83	9.97	**8.71**	**8.52**	18.25	16.74
10(25)	8.12	7.01	5.66	9.65	23.06	21.75	10.65	10.87	**9.43**	**7.57**	20.79	19.46
11 (24)	6.73	7.12	8.09	10.73	24.75	23.57	11.16	11.37	**10.34**	**9.51**	22.97	21.80
12(23)	7.78	8.63	6.59	10.39	26.47	25.44	11.80	10.87	**11.02**	**9.29**	24.77	23.73
13(22)	8.05	9.52	7.56	9.63	28.34	27.41	13.43	13.74	**12.07**	**9.86**	26.04	25.10
14(21)	9.37	10.93	**6.71**	**8.76**	30.60	29.74	14.44	12.90	**12.98**	**9.01**	27.39	26.53
15(20)	9.91	12.18	**6.56**	**8.01**	32.08	31.32	15.91	16.08	**12.46**	**9.49**	30.30	29.55
16(19)	11.62	13.20	**6.71**	**7.49**	33.76	33.06	16.32	15.79	**11.84**	**8.99**	33.22	32.54
17(18)	12.90	14.08	**8.45**	**8.42**	35.30	34.67	15.13	16.71	**11.69**	**8.82**	36.57	35.95
18(17)	13.23	14.54	**9.22**	**7.86**	36.81	36.23	16.28	17.94	**11.41**	**7.32**	39.81	39.24
POOLED	**7.25**	**5.36**	**5.95**	**5.85**	**22.07**	**20.66**	**10.24**	**8.06**	**9.07**	**6.81**	**19.52**	**18.10**
UK							Germany					
1(34)	0.67	0.63	8.30	3.24	0.73	14.88	2.17	2.32	3.61	3.56	2.28	45.14
2(33)	1.15	1.11	9.39	4.57	3.74	4.04	4.07	4.41	5.13	4.75	5.37	15.34
3(32)	1.84	1.41	10.23	5.80	6.57	1.61	6.19	5.15	5.70	6.36	10.54	3.65
4(31)	2.00	1.65	10.70	7.08	9.04	5.28	8.15	7.74	**7.87**	**6.64**	14.41	6.51
5(30)	2.81	2.06	10.98	8.29	11.35	8.31	8.16	9.25	9.39	7.68	20.01	11.79
6(29)	3.07	2.20	11.33	9.36	13.80	11.31	8.73	9.43	10.83	8.71	22.71	17.19
7(28)	3.41	2.37	11.64	10.48	16.53	14.48	10.90	12.66	12.31	10.46	25.61	20.76
8(27)	3.59	3.47	11.93	11.49	18.78	17.02	12.93	15.13	13.75	11.56	28.39	24.15
9(26)	4.74	3.83	12.13	12.27	20.22	18.71	14.16	18.65	15.64	12.63	32.02	28.48
10(25)	5.05	4.51	12.18	12.95	22.14	20.79	15.22	21.43	16.69	13.21	35.20	31.62
11 (24)	4.92	5.39	12.80	13.53	24.00	22.81	18.11	21.75	19.98	14.74	38.39	35.57
12(23)	5.73	5.57	13.22	14.09	26.32	25.24	20.77	22.72	21.52	15.63	40.82	38.25
13(22)	7.09	4.96	13.86	14.54	28.19	27.24	22.86	29.47	20.68	14.30	43.67	41.55
14(21)	7.44	7.54	14.08	15.00	29.73	28.85	27.71	38.66	**19.55**	**15.28**	47.38	45.29
15(20)	7.60	8.44	14.23	15.52	31.62	30.83	35.08	44.71	**19.33**	**8.92**	49.95	48.08
16(19)	8.37	8.04	14.08	15.82	33.43	32.70	41.09	49.16	**19.05**	**7.93**	52.25	50.58
17(18)	9.79	9.76	14.33	15.94	35.06	34.40	47.94	59.79	**16.73**	**7.08**	53.92	52.33
18(17)	10.87	11.00	14.42	15.85	36.54	35.94	54.92	71.51	**13.81**	**6.22**	56.08	54.69
POOLED	**4.83**	**3.56**	**12.15**	**10.48**	**21.18**	**19.75**	**14.69**	**17.02**	**14.73**	**9.00**	**33.59**	**33.61**

The rows labeled "Pooled" show the median/geometric mean of the rows above them, for each country and model. The first column shows the number of steps ahead, *L*, by row, with the number of observations in the sample in brackets. Bold values indicate the steps for which the Bemmaor model accuracy measures (median and geometric mean) are better than the Bass model ones.

the errors of their sample series. However, this property is valid only for up to three-step-ahead forecasts.

Our data (which are also evaluated for longer horizons) provide different results, as the accuracy of the first step for the Bemmaor model is lower than that for the Bass model, though similar, for all countries analyzed. Furthermore, for all countries except for the UK, the Bemmaor model is more accurate for all horizons longer than one step ahead. Moreover, the Bemmaor model produces better forecasts in terms of the global measures, such as median and geometric mean errors, at the longer horizons: for the US from 14 steps ahead; for France from eight steps ahead; and for Germany from 14 steps ahead. However, for the UK, the Bass model outperforms the Bemmaor one in all cases.

6. Conclusions

6.1. Discussion of the results

The estimation results reported in Table 1 clearly show that the estimates for the shape parameter, $\beta = q/p$, differ significantly across countries under the hypotheses of the Bass model, highlighting the differences across countries in the speed and modalities of MSN diffusion. In particular, we found that the slowest diffusion speed of MSN occurred in Germany, the country with the largest Bass shape parameter, followed by France, the US and the UK.

Fig. 2 shows the estimation and forecasts of the numbers of adoptions, using both the Bass and Bemmaor models, for the four countries analyzed. For the French adoption data only, we can say that the Bemmaor model reduces to a Bass one, as the estimate of the shape parameter, α, is close to one ($\alpha = 1.0302$).

As was discussed in the previous sections, in the context of a Bass model, higher values of q and lower values of p, leading to higher values of the shape parameter q/p, may be indicative of the presence of network externalities and threshold effects, as fewer people adopt independently, due to the low p, and more adopt only after others have adopted, because of the high q.

In all four countries analyzed, the ratio q/p is well above one, as is reflected in the S-shaped distribution of cumulative adoptions of MSN in Fig. 2, which displays a clear *left skew*. However, our estimates still show large differences in q/p ratios across countries.

The estimation of the two different models, namely the Bass and Bemmaor models, allows us to refine our diffusion analysis by comparing the speeds of diffusion of MSN across countries, while also taking into account the effects of their *skew*-parameters α.

The MSN diffusion speed is clearly linked to the value of the shape parameter q/p, as the share of innovators is greater than that of imitators in the early stages of adoption. For example, although Germany and the US have comparable *skew* parameters,[11] Fig. 3[12] shows that Germany has a lower diffusion speed than the US. Indeed, the S-shape for Germany is more pronounced than that for the US, as there is more *left skew* accompanying the German adoption peak,[13] which occurs well after the US one (February 2012 versus December 2010).

This evidence can be interpreted in terms of Mahler and Rogers' (1999) description of the diffusion of interactive innovations. In their view, a *left skew* accompanied by a later adoption peak indicates the presence of network effects that are due to the interactive nature of the innovation. In the case of the adoption of the same technology across two different countries, one can relate the observed differences in the diffusion process to underlying cultural, nationally specific characteristics that affect the degree of interaction among users of the same technology, along the lines of Van den Bulte and Stremersch (2004), who explicitly included nation-specific, cultural covariates in their estimation of diffusion models.

Moving to the analysis of the estimated values for the *skew* parameters α across the four different countries, we note that, apart from France, all of the countries have estimated skew parameters α that are smaller than one, indicating the presence of a greater degree of heterogeneity in individual predispositions to adopt than that assumed implicitly in the Bass model.

Our estimates for the UK, Germany and the US all show the presence of an "extra Bass" *skew*, due to heterogeneity in the adoption propensity among their populations. However, Fig. 2 shows that, while the values of α are smaller than one for all countries except France, all of the cumulative diffusion curves remain S-shaped and *left skewed*. These overall *left skews* provide evidence for the existence of network externalities for MSN adoption, due to low p and high q values, even when accounting for the otherwise contrasting effects due to the high heterogeneity, captured by the estimated low values of the skew parameters α.

Fig. 4 shows the estimated (April 2007 to Oct 2012) and forecasted (November 2012 to November 2016) graphs for the period percentage adoptions.

The rates of diffusion of MSN in these four G7 nations show differences that are consistent with the findings of Van den Bulte and Stremersch (2004). Unfortunately, though, it is difficult to identify the independent factors influencing contagion/innovation and heterogeneity. However, Germany has a speed of diffusion that is lower than that of the US, which has a similar heterogeneity. As a result, the German S-shaped diffusion curve is more pronounced, showing evidence of network externalities requiring a critical mass of adopters before reaching the peak, due to the higher value of its shape parameter (cf. Fig. 3).

It is also interesting to note from Fig. 4 that the UK, which has the smallest q/p ratio, has the highest proportion of initial adopters, certainly due to the large value of its innovation parameter, p. The second-highest initial adoption ratio is in the US, which similarly has the second-lowest q/p ratio. Germany and France display similar lower initial adoption rates, clearly due to them having the two largest, but significantly different, q/p

[11] As the 95% confidence interval for the US value of α (0.3841, 0.6892) includes the German *skew* point estimate ($\alpha = 0.573$)

[12] Displaying the cumulative estimation up to October 2012, and forecasts since November 2012 for the two main diffusion models.

[13] For calculations of the peak adoption time T^*, see the Appendix, derived from Bemmaor (1994).

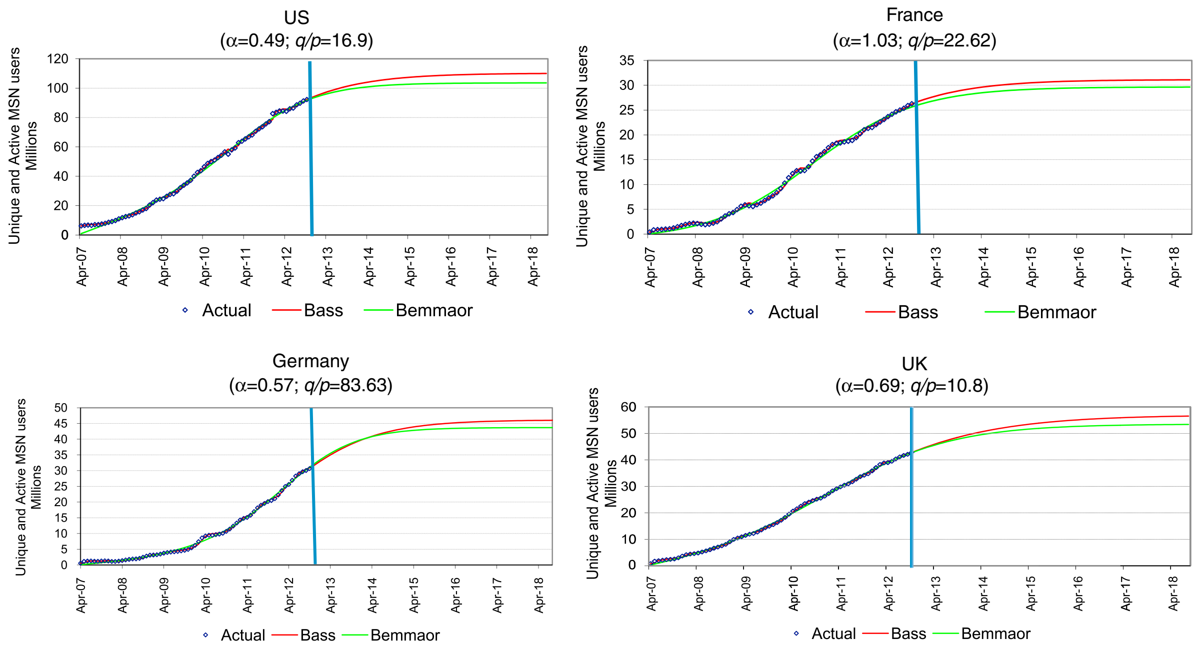

Fig. 2. Actual values, fitted values and forecasts. Forecasting sample: November 2012 to April 2018. The Bass model shape parameter (q/p) and the Bemmaor model *skew* parameter (α) are derived from Table 1.

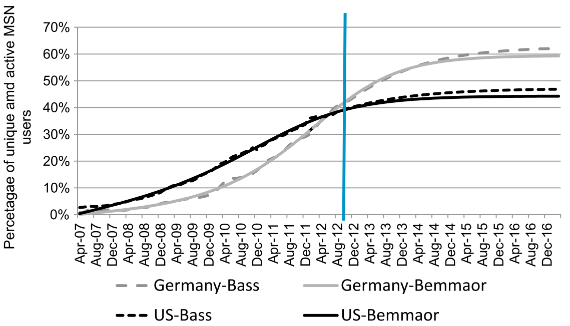

Fig. 3. Estimations and forecasts of the percentage of unique and active MSN users, using the Bass and Bemmaor models for the US and Germany.

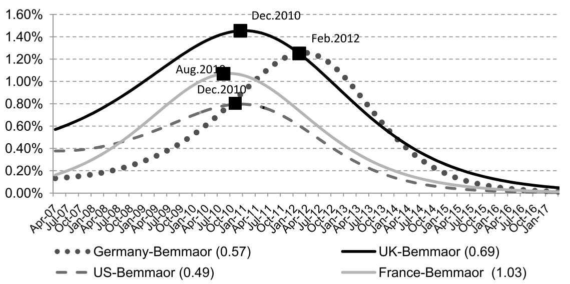

Fig. 4. Estimated values and forecasts of the first differences (in percentages) of cumulated active and unique users of MSN, with the corresponding T^* (adoption peak), using the Bemmaor model for Germany, the US, the UK and France; the *skew* parameter (α) is given in brackets.

ratios. However, Germany's adoption peak occurs later than France's, reflecting the more pronounced *left skew* due to the higher value of the German shape parameter q/p.

6.2. Implications, limitations and further research

The increased demand for real-time communication between SN members could be an important driver of the adoption of 3G and 4G mobile broadband, and MSN could increase the utility of these enhanced broadband services further and drive adoption. This paper has studied MSN diffusion across four countries, with a focus on the differences in their patterns of diffusion, and discussed the emerging evidence of network externalities.

We have seen that critical mass and network externalities were present in each of the four countries, but that while these were captured within a Bass model framework for France, pointing towards the high presence of imitators, the other countries also showed a contrasting "extra-Bass" effect due to heterogeneity in the individual propensity to adopt, as captured by the Bemmaor model.

This evidence is relevant for assessing the indirect role that MSN externalities play in the observed processes of diffusion of the latest generation of mobile broadband. One could expect a slow-down in both MSN diffusion and the adoption of the latest generation of mobile broadband for countries that show a greater sensitivity to network externalities in the diffusion of MSN. These indicators are captured by the different peak times of adoption discussed in this paper. The importance of studying these "chilling effects of networks externalities" (Goldenberg, Libai, & Muller, 2010) relates to their potential negative impact on the adoption of the latest generation of mobile broadband.

The data used to estimate MSN diffusion across the four countries focus on a clearly interactive technology, based on bilateral links across social network users. These underlying network relationships and their implied topologies are not observed in our data directly, but still affect their diffusion processes, as was observed by Susarla, Oh, and Tan (2012). These authors "consider diffusion in the context of a community where the diffusion process propagates through proximate links in a network", and quantify the impact of the social network structure on the diffusion of videos on Youtube. Similarly, Dover, Goldenberg, and Shapira (2012) proposed a method of capturing these network effects by using penetration data only. Future research on MSN diffusion should extend our current analysis by encompassing these methods, with the aim of assessing the potential effects of the underlying unobserved network characteristics on the shape of the diffusion process, improving our understanding of the key factors underlying the presence or absence of critical mass effects. The evaluation and discrimination of global word of mouth effects from network externalities will also be relevant, as was suggested by Goldenberg et al. (2010), and, as Islam and Meade (2012) showed, the cross country analysis should be extended by using a pooled estimation strategy to capture the cross country heterogeneity and to shed light on the reasons for the persistence of countries that lead and lag in "adoption".

Acknowledgments

We would like to thank Professors Albert Bemmaor and Nigel Meade warmly for their helpful comments and suggestions. We would also like to thank two anonymous referees for their valuable suggestions and carefully provided advice. Of course, the usual disclaimer applies. Finally, we are grateful to comScore Inc for providing us with data about MSNs, and to Michael Leonard and Marc Kessler from SAS Institute and to Dr. Alison Hirst and Dr. Antonio Sanchez-Vazquez for editorial assistance.

Appendix

The estimation of T^* for the Bemmaor model (Gamma/ Shifted Gompertz) is obtained as follows (see Bemmaor, 1994):

$$T^* = (-1/b)\ln x^*, \quad 0 < x^* < 1$$
$$\text{with } x^* = (-B + \sqrt{\Delta})/2A$$
$$A = -\beta(\alpha-1)^2, \qquad B = \beta\alpha^2 + 3\alpha - 2$$
$$\Delta = \alpha(\beta^2\alpha^3 + 2\beta\alpha^2 + 4\beta\alpha + 5\alpha - 4\beta - 4), \quad \Delta \geq 0.$$

References

Allen, D. (1988). New telecommunications services: Network externalities and critical mass. *Telecommunications Policy*, *12*(3), 257–271.

Arthur, W. B. (1989). Competing technologies, increasing returns, and lock-in by historical events. *The Economic Journal*, *99*(394), 116–131.

Bartels, R., & Islam, T. (2002). Supply restricted telecommunications markets: the effect of technical efficiency on waiting times. *Journal of Productivity Analysis*, *18*(2), 161–169.

Bass, F. M. (1969). A new product growth model for consumer durables. *Management Science*, *15*(5), 215–227.

Bauckhage, C., Kersting, K., & Rastegarpanah, B. (2014). Collective attention to social media evolves according to diffusion models. In *Proceedings of the companion publication of the 23rd international conference on world wide web companion* (WWW Companion'14). (pp. 223–224). Switzerland: International World Wide Web Conferences Steering Committee, Republic and Canton of Geneva.

Bemmaor, A. C. (1994). Modeling the diffusion of new durable goods: Word-of-mouth effect versus consumer heterogeneity. In G. Laurent, G. L. Lilien, & B. Pras (Eds.), *Research traditions in marketing* (pp. 201–223). Boston, MA: Kluwer Academic Publish Group.

Bemmaor, A. C., & Lee, J. (2002). The impact of heterogeneity and ill-conditioning on diffusion model parameter estimates. *Marketing Science*, *21*(2), 209–220.

Boyd, D. M., & Ellison, N. B. (2007). Social network sites: Definition, history, and scholarship. *Journal of Computer-Mediated Communication*, *13*(1), 210–230.

Chatterjee, R., & Eliashberg, J. (1990). The innovation diffusion process in a heterogeneous population: a micromodeling approach. *Management Science*, *36*(9), 1057–1079.

David, P. (1985). Clio and the economics of the QWERTY. *The American Economic Review Proceedings*, *75*(2), 332–337.

Dover, Y., Goldenberg, J., & Shapira, D. (2012). Network traces on penetration: uncovering degree distribution from adoption data. *Marketing Science*, *31*(4), 689–812.

Funk, J. L. (2007). Solving the startup problem in Western mobile Internet markets. *Telecommunications Policy*, *31*(1), 14–30.

Funk, J. L. (2011). Standards, critical mass, and the formation of complex industries: A case study of the mobile Internet. *Journal of Engineering and Technology Management*, *28*(4), 232–248.

Giovannetti, E. (2000). Technology adoption and the emergence of regional asymmetries. *The Journal of Industrial Economics*, *48*(1), 71–102.

Giovannetti, E. (2013). Catching up, leapfrogging or forging ahead? Exploring the effects of integration and history on spatial technological adoptions. *Environment and Planning A*, *45*(4), 930–946.

Goldenberg, J., Libai, B., & Muller, E. (2010). The chilling effects of network externalities. *International Journal of Research in Marketing*, *27*(1), 4–15.

Grajek, M., & Kretschmer, T. (2012). Identifying critical mass in the global cellular telephony market. *International Journal of Industrial Organization*, *30*(6), 496–507.

Grove, N., & Baumann, O. (2012). Complexity in the telecommunications industry: When integrating infrastructure and services backfires. *Telecommunications Policy*, *36*(1), 40–50.

Hyndman, R. J., & Athanasopoulos, G. (2014). *Forecasting: principles and practice*. OTexts, retrieved from http://OTexts.org/fpp/.

Informa (2012). Contents & services interactive forecasting tool.

Islam, T. (2014). Household level innovation diffusion model of photo-voltaic (PV) solar cells from stated preference data. *Energy Policy*, *65*, 340–350.

Islam, T., & Fiebig, D. (2001). Modelling the development of supply restricted telecommunications markets. *Journal of Forecasting*, *20*(4), 249–264.

Islam, T., Fiebig, D. G., & Meade, N. (2002). Modelling multinational telecommunications demand with limited data. *International Journal of Forecasting*, *18*, 605–624.

Islam, T., & Meade, N. (2012). The impact of competition, and economic globalization on the multinational diffusion of 3G mobile phones. *Technological Forecasting and Social Change*, *79*(5), 843–850.

Katz, M. L., & Shapiro, C. (1985). Network externalities, competition, and compatibility. *The American Economic Review*, *75*(3), 424–440.

Katz, M. L., & Shapiro, C. (1986). Technology adoption in the presence of network externalities. *Journal of Political Economy*, *94*(4), 822–841.

Kim, Y. (2011). The contribution of social network sites to exposure to political difference: The relationships among SNSs, online political messaging, and exposure to cross-cutting perspectives. *Computers in Human Behavior*, *27*(2), 971–977.

Mahajan, V., & Muller, E. (1979). Innovation diffusion and new product growth models in marketing. *Journal of Marketing*, *43*(4), 55–68.

Mahajan, V., Muller, E., & Srivastava, R. (1990). Determination of adopter categories by using innovation diffusion models. *Journal of Marketing Research*, *28*, 37–50.

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*(10–11), 717–740.

Mansfield, E. (1961). Technical change and the rate of imitation. *Econometrica*, *29*, 741–766.

Meade, N., & Islam, T. (2006). Modelling and forecasting the diffusion of innovation—A 25-year review. *International Journal of Forecasting*, *22*(3), 519–545.

Meade, N., & Islam, T. (2008). The effects of network externalities on the diffusion of cellular telephones. *Telektronikk: Telecommunications Forecasting*, *3*(4), 74–81.

Peers, Y. (2011). *Econometric advances in diffusion models.* No. EPS-2011-251-MKT, Erasmus Research Institute of Management (ERIM).

Peres, R., Muller, E., & Mahajan, V. (2010). Innovation diffusion and new product growth models: a critical review and research directions. *International Journal of Research in Marketing*, *27*(2), 91–106.

Rogers, E. M. (1962). *Diffusion of innovations* (1st ed.). New York: The Free Press.

Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). New York: The Free Press.

Srinivasan, V., & Mason, C. H. (1986). Technical note—nonlinear least squares estimation of new product diffusion models. *Marketing Science*, *5*(2), 169–178.

Stremersch, S., Muller, E., & Peres, R. (2010). Does new product growth accelerate across technology generations? *Marketing Letters*, *21*(1), 103–120.

Stremersch, S., Tellis, G. J., Franses, P. H., & Binken, J. L. G. (2007). Indirect network effects in new product growth. *Journal of Marketing*, *71*(3), 52–74.

Susarla, A., Oh, J.-H., & Tan, Y. (2012). Social network and the diffusion of user-generated content: evidence from Youtube. *Information Systems Research*, *23*(1), 23–41.

Van den Bulte, C. (2002). Want to know how diffusion speed varies accros countries and products? Try using a Bass model. *Product Development and Management Association, PDMA Visions*, *26*(4), 12–15.

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.

West, J., & Mace, M. (2010). Browsing as the killer app: Explaining the rapid success of Apple's iPhone. *Telecommunications Policy*, *34*(5–6), 270–286.

Miriam Scaglione is professor at the School of Management and Tourism at the University of Applied Sciences and Arts of Western Switzerland, Valais. She teaches a marketing in tourism B.Sc. program, and multivariate analysis in the MBA program. She is also a researcher at the Institute of Tourism at the same university. She earned a Ph.D. in Computer Science and an M.Sc. in Statistics (Université de Neuchâtel); an M.Sc. in Cognitive Sciences (EHSS, Paris); and a B.Sc. in Scientific Computing and a B.Sc. in Mathematics and Astronomy (Universidad de Buenos Aires). She has published in *Technovation* and the *Journal of Transportation and Statistics*; and she won the Emeral Tourism Review 2012 award for the best research at the 62nd International Association of Scientific Experts in Tourism conference. Her interests are in e-tourism, tourism forecasting and technological forecasting.

Emanuele Giovannetti, Ph.D. (Cantab), is Professor in Economics at Anglia Ruskin University. His research focuses on competition policy in network industries. Emanuele has published in various leading journals including *The Economic Journal*, *Environment and Planning A*, *International Economic Review*, *International Journal of Industrial Organization*, *Journal of Industrial Economics*, *International Journal of Production Economics*, *Journal of Economic Surveys*, *Information Economics and Policy*, *Spatial Economic Analysis*, and *Journal of Competition Law and Economics*. He edited the special issue of *Telecommunications Policy* on "Peering and Roaming in the Internet", and co-edited "The Internet Revolution: A Global Perspective" for Cambridge University Press.

Mohsen Hamoudia is head of Strategy and Market Intelligence of the large projects division within Orange Business Services, Paris. Prior to holding this position, he was head of the forecasting division of France Telecom Long Distance, Paris (1996–2001). He has been teaching forecasting and quantitative techniques since 1989 at Toulouse Business School, ESDES Business School of Lyon and ISM (Institut Supérieur du Marketing), Paris. Mohsen's research interests include the forecasting and empirical aspects of information and communications technologies (ICT) and telecommunications, airline industry and innovation forecasting. He is a member of the international editorial board of *Telecommunications Policy Journal* (Elsevier) and has been president of the International Institute of Forecasters (IIF) since 2012.

Please cite this article in press as: Scaglione, M., et al., The diffusion of mobile social networking: Exploring adoption externalities in four G7 countries. International Journal of Forecasting (2015), http://dx.doi.org/10.1016/j.ijforecast.2015.03.005