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Predicting Repeat and Total Visits to a Destination Using Simulation Modeling Through Time

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Abstract

Previous literature has shown that important variations exist over time regarding the extent to which visitors make return trips to tourist destinations. This paper provides an analytical framework to account for time discrepancies in behavior and helps predict repeat visits to a destination at different time points. The authors carried out an empirically validated three-parameter Weibull distribution and a 50-period numerical simulation exercise to illustrate ways in which the pattern of repeat visits affects total visitors through time. Several scenarios representing different distribution parameters and different intensities of initial trips are illustrated. Implications for destination managers and future research extensions are suggested.

Keywords: Repeat visits, tourist destinations, recency-frequency theorem, simulation.

Introduction

Repeat visits are an important element of tourism for both the economy as a whole and the individual tourist attraction. According to a 2005 report by the English Tourist Board (ETB), 79% of all overseas visitors to the United Kingdom made a repeat visit over the period 1994-2004. For leisure visitors only, the percentage for the same period dropped to 60%. Individuals visiting friends and family (VFRs), had the highest percentage of repeat visits (84%), and the percentage across all visitor types increases with the visitor's age: in the 16- to 24-year-old category, 12% made repeat visits, while the percentage rises to 39% for those older than 45. A later customer survey by the ETB (2007) stated that 28% of overseas visitors had visited London between two and five times in the preceding five years. Visitor surveys at individual tourist attractions have emphasized the significance of repeat visits; at the British Museum for example, a visitor survey (Caygill & Leese, 1994) for 1992-1993 showed that in June 1993, 51% of visitors had made an earlier visit, and 22% had made six or more visits in the previous 12 months.

The importance of repeat visits has been further identified in the findings of econometric studies of both international tourism flows (e.g., Akal, 2004; Cho, 2003; Johnson & Ashworth, 1990) and the demand for individual attractions (e.g., Darnell, Johnson, & Thomas, 1990, 1998). These studies illustrate the important explanatory role that lagged dependent variables play in predicting visits, such that a visit in a current period affects the likelihood of a repeat visit by the same visitor in a subsequent period. Econometric models in tourism, however, have not differentiated between categories of visitors (e.g., repeat and non-repeat). Tourism forecasting, however, has usually used parameters such as income, price, exchange rate, time availability, and discretionary income. Factors such as frequency and recency of visits have been neglected, however, because of their inherent complexity (Li, Hong, & Witt, 2006; Sinclair & Stabler, 1997; Song & Witt, 2003).

Some studies have used Markov chains to analyze patterns and structures of travelers' flows to a destination (Baloglu & Erickson, 1998; Beaman, Kozak, & Huan, 2001; Taplin, 2003) and to specific attractions (Xia, Zeephongsekul, & Arrowsmith, 2008). These chains apply first-order dependence to examine the dynamics between different events, such as a first-time visitor becoming a frequent, repeat visitor. Markov studies, however, have relied on initial-state probabilities that assumed homogeneous transition probabilities through time. This contradicts the frequency-recency theorem, which previous tourism literature has shown that tourists that have visited a destination more recently are more likely to return and that the likelihood of returning decreases over time (Hughes, 1995). This also contradicts other previous exploratory studies on revisits (Baloglu & Erickson, 1998; Gyte & Pheps, 1989; Oppermann, 1997). For example, Oppermann's (1997) study on New Zealanders' visits to Australia argued that a close relationship exists between past and current behavior, indicating recent visitors have a greater likelihood of returning in the future. Moreover, although studies using Markov chains reveal the quantity of first-time visitors that are likely to become repeats visitors over time (recurrent and less-recurrent) and vice versa, they do not provide a tool to determine the number of revisits (and subsequently the total number of visits) to a destination at specific point in time. These studies are thus are of limited practical use to destination managers.

Acknowledging the importance of entrance and exit flows, Darnell and Johnson (2001) approximated a mathematical schema to measure repeat and total visits to an attraction. They placed an upper limit on return trips, however, and their model did not include variable return frequencies to account for the time nor visit history, as does the Markov approach.Consequent to its simplistic assumptions, Darnell and Johnson's (2001) paper did not provide a realistic tool to determine the number of revisits (and subsequently the total number of visits) to a destination at specific point in time. Again, this approach is of limited practical use to destination managers.

Clearly, little research has focused on predicting destination choice based on consumer type, for example, first versus repeat travelers, combined with varying time behavior. This study attempts to fill this gap by evaluating realistically the way in which initial visits to a destination induce repeat visits and thus affect the flow of visits to that destination over time.

This paper is organized as follows. Section 2 establishes an analytical framework by approximating the temporal return likelihood of travelers to a sunny destination over five time periods using a three-parameter Weibull density function. Data is taken from a study of French, German, and English travelers surveyed in December 2009 that had visited a sunny destination for the first time prior to the survey. Pilot studies conducted prior to the December 2009 survey calibrated the time periods for revisit intent to provide the most inclusive time intervals for revisits to occur. Section 3 presents a simulation showing the ways in which the pattern of repeat visits can affect the total flow of visits through time. The present study concludes by considering implications and suggesting avenues for future work.

This study's aim is to shed light on a new tool that can realistically predict visitors' probability of visiting a specific location more than once. It does so by empirically—that is, using data to validate Weibull probability distribution function for returns—considering the impact of diminishing returns induced by an initial visit over time. The use of this tool could provide an invaluable advantage to destination managers and marketers. For tourism destination managers, it could provide improved knowledge about expected total demand and vital information regarding infrastructure requirements, demand-adjusted pricing, positioning strategy, and other key decision points. This tool can help tourism marketers channel valuable financial resources toward potential consumers that are most likely to return to an area, while avoiding expenditures on those that will either definitely not visit again or have already decided to visit again. This analytical approach can also be applied to tourist attractions and activities, not merely destinations.

Analytical Framework

1) Temporal Dimension of First-Time Visits

This paper starts by examining the temporal dimension of an initial visit to a destination, undertaken by individual i at time j. Subsequent to his/her first visit, individual i may decide to either return or not return to that destination in the future. If the purpose of a traveler's first visit is to gather information in order to decide about a second visit (Milman & Pizam, 1995; Um & Crompton, 1992; Woodside & Lysonki, 1989), such an individual can be described as a checking-it-out (CIO) visitor and is likely to return in the future if he liked the destination. If the purpose of a first trip is to see or visit a particular site, the visitor may be described as a one-time only (1TO) visitor (Uysal & Hagan, 1993) and is likely not to return, at least not in the near future.

If Xi represents an individual's likelihood of not returning, then $(1-X_i)$ represents the individual's likelihood of revisiting. Thus, X_i represents the probability of a CIO tourist not liking the destination for one reason or another and deciding not to return; thus, it also represents the probability of a first-time visitor being a 1TO tourist. Likewise, $(1-X_i)$ represents the probability of a CIO tourist liking the destination and deciding to return. Further, if M_j persons initially visit a destination at time j, the M_j population is composed of individuals who have different characteristics and thus different probabilities of returning at any time t > j. Hence, the total number of returns at different time points, t, is given by $\sum_{i=1}^{Mj}(1-X_i)\times \Pr_i\{v_{t-j}\}$, where, t-j represents the time distance between the initial and return visit times to a destination.

To trace and simplify the analysis, we assume that the population visiting a destination is homogeneous. This supposition is supported by Oppermann (2000a), who argued that first-time tourists at a destination are, in a way, homogeneous because none have experience with the destination. Consequently, many tourism models in previous literature have presumed homogeneity among visitors (Baloglu & Erickson, 1998; Kozak, Huan, & Beaman, 2002). As a result, the individuals in our model have the same likelihood of returning, (1-X) and equal probability of return, $\Pr\{v_{t-j}\}$ at various time points, t. Thus, if M_j is the number of initial visitors to a destination at time j, the number of revisits at any time t<T+j, induced by M_j, is given by $M_j \times (1-X) \times \Pr\{v_{t-j}\}$. Where, T+j, represents an upper-limit point in time after which travelers will not likely return. Thus, T is the time interval for revisits to take place. The tourism literature supports this approach, including Oppermann (1998), who argued that as more time passes, the intent to revisit diminishes and, at a certain point, that intent vanishes.

2) Total Number of Visits at Time t

Next, we can use the expression of the number of revisits at any time, t, induced by Mj presented above, to calculate the total number of visitors, Vt, at any time, t, which is given by the initial arrival at time t plus all revisits, such that:

$$V_t = M_t + \sum_{j=0}^{t} M_j \times (1-X) \times \Pr\{v_{t-j}\}, \ \forall j < t,$$

Where, Mj represents the initial number of visitors at time j, and $\Pr\{v_{t-j}\}$ represents the probability of revisits at time t for the population initially visiting at time j.

Table 1 presents a schematic representation of the total number of visitors at any time t, Vt. Beyond time T, which is equivalent to the interval between revisits and any time point T+j, returns since the earliest period are replaced by revisits from the latest period. In this way, the number of total revisits remains steady in the case of a constant flow of initial visits, Mj. For example, at time T+1, visitors from period 0 cease to return, while initial visitors from period T begin revisiting in T+1 with probability (1-X) × Pr{V1}. Thus, for equal initial visits, Mj, $V_{T+1} = M_j \times (2-X) = V_T$, remains constant or steady as shown below.

Table 1: A Schematic Representation of the Total Number of Visitors at any Time t, V_t.

	0	1	2	3	T	T+1
0	M_0	M_0* (1-X) *Pr(v_1)	M_0*(1-X) *Pr(v_2)	M_0* (1-X) *Pr(v_j)	M_0* (1-X) *Pr(v_T)	
1		M_1	M_1* (1-X) *Pr(v_{2-1})	M_1* (1-X) *Pr(v_{j-1})	M_1* (1-X) *Pr(v_{T-1})	M_1 * (1-x) *Pr(v_T)
2			M_2	M_2* (1-X) *Pr(v_{j-2})	M_2 * (1-X) *Pr(v_{T-2})	M_2* (1-X) *Pr(v_{T-1})
3				M_3	M_3 * (1-X) Pr(v_{T-3})	M_3* (1-X) *Pr(v_{T-2})
J					M_j * (1-X) *Pr(V_{T-j})	M_j* (1-X) *Pr(V_{T+1-j})
T-2					M_{T-2} * (1-X) *Pr(V_2)	M_{T-2}* (1-X) *Pr(V_3)
T-1					M_{T-1} * (1-X) *Pr(V_1)	M_{T-1}* (1-X) *Pr(V_2)
T					M_T	M_T* (1-x) *Pr(V_1)
T+1						M_{T+1}
Vt	**M0**	**M_1 + M_0* (1-X) *Pr(v_1)**			**(i)**	**(ii)**

(i) $V_T = M_0*(1-X)*\Pr(v_T) + M_1*(1-X)*\Pr(v_{T-1}) + M_2*(1-X)*\Pr(v_{T-2}) + \ldots + M_j*(1-X)*\Pr(V_{T-j}) + \ldots + M_{T-2}*(1-X)*\Pr(V_2) + M_T*(1-X)*\Pr(V_1) + M_{T+1}$
VT= M * (1-X) * F(T: λ, K, j) = M * (2-X) For equal initial arrivals, Mj

(ii) $V_{T+1} = M_1*(1-X)*\Pr(v_T) + M_2*(1-X)*\Pr(v_{T-1}) + \ldots + M_j*(1-X)*\Pr(V_{T+1-j}) + \ldots + M_{T-2}*(1-X)*\Pr(V_3) + M_{T-1}*(1-X)*\Pr(V_2) + M_T*(1-X)*\Pr(V_1) + M_{T+1+2}$
VT+1= M * (1-X) * F(T+1: λ, K, j)= M * (2-X) For equal initial arrivals, Mj

3) Probability Function of Revisits over Time

Next, it would be useful to identify the time frame T, during which the revisits occur and the revisit probabilities between time j and T+j. This will suggest the number of revisits at each interval between j and T+j. For this purpose, an online questionnaire was administered in December 2009 to French, English, and German travelers aged 18 years and older. Survey participants were chosen from panels of respondents that represent each country's aggregate demographics. Because well-established destinations represent the ideal ground for testing repeat visitations across time (Kozak, 2001), a screening question asked whether respondents had taken at least one plane trip (of at least two hours) to visit a sun destination for the first time in the six months prior to the survey. This filter question helped reduce bias related to extreme travel behaviors caused by respondents visiting proximate domestic destinations, defined as less than two hours by car or other transportation, planes excluded), which might confuse the analysis. Moreover, given the survey timeframe, six months represented the ideal time to visit the type of destination of interest; thus, this timing was designed to help improve response rates.

Choosing a time frame for the study was an important decision because prior literature includes no single accepted definition of time frame during which revisits might occur (Ajzen, 1991; Eagley & Chaiken, 1993; Feng & Jang, 2007). Pilot studies conducted for the December 2009 survey calibrated the time periods for revisit intent to provide the most inclusive time intervals for revisits and indicated that intent to return can be measured using five time periods—in year 1; in year 3; in year 5; in year 10; and in year 20. Respectively, these correspond to immediate, short-, mid-, and long-term, which covers return intentions over all possible times.

The questionnaire included two sections. In the first section, a series of travelers' information questions, including gender, age, occupation, and trip characteristics, such as travel party, were asked to develop the travelers' profiles. In the second section, respondents were asked about the number of times they expected to return in the coming 20 years to the destination they had previously specified as their first-time visit six months prior to the survey. Also in this second section, respondents were also asked about their intent to return as measured according to the five time periods as noted above. These time periods were found to represent the time intervals during which revisits can occur. These later questions were measured using a 7-point Likert scale ranging from 1 = *very unlikely* to 7 = *very likely*. The literature supports the wide-range Likert scale because it ensures that the data are close to being continuous **(**Johnson & Ashworth, 1990).

In total, 1,500 questionnaires were delivered to generate a final sample of 450 usable surveys (150 from each nationality), resulting in an average response rate of 29.4%. A detailed sample profile is displayed in Table 2. The mean age of the respondents was 38, with a minimum age of 18 and a maximum of 69. Male (51.3%) and female (48.7%) respondents were represented equally. Nearly two-thirds (61.1%) of respondents mentioned having traveled with a partner/spouse or children or with spouse and children, which is typical for this type of destination/trip (La Mondia, Snell, & Bhat, 2009), whereas 22.8% travelled with other friends or relatives and only 10.1% traveled alone. Professionals (30.3%), skilled (22.1%) and unskilled (18.2%) labor, executives/managers (16.1%), and students (10.4%) were the respondents' main occupations. These figures are similar to those in previous studies reported in the travel and tourism literature (Bigne, Sanchez, &

Sanchez, 2001; Vassiladis, 2008). Finally, respondents mentioned they expected to return 10 times, on average, to the destination they had previously specified as their first-time visit six months prior to the survey.

Data from the survey was then analyzed using @Risk 7.0, using the distribution fitting function specifying continuous absolute sample. Results of the analysis showed the probability function for return, $\Pr\{v_{t-j}\}$, at any time t following an initial visit at time j, approximates a three-parameter Weibull density function: $f(t:\lambda, k, j) = \frac{k}{\lambda} \times (\frac{t-j}{\lambda})^{k-1} \times e^{-(t-j/\lambda)^k}$ for $t \geq$ j, and f(x; k; λ) = 0 for $t <$ j , With k = 0.8 representing the shape parameter; λ = 10 representing the scale parameter showing the average number of revisits per individual over a given time period; and j being the location parameter of the distribution (McCool, 1998). j also reflects the time of first visits, such that t-j indicates the elapsed time prior to returning. To make the analysis more observable, we assumed similar characteristics for the destinations through time. Thus, the revisits probability function, $f(t: \lambda, k, j)$, did not account for destination-specific characteristics such as available attractions and facilities, distance and travel time from the individual's home, marketing efforts, and so on through the intensity of first visits, M_j, and return parameters, λ and k.

In this example of the timing and likelihood of tourists' returning to a destination, with k= 0.8, a decreasing return rate is implied, signifying that travelers tend to return quickly to a destination, with the revisit rate decreasing as time goes on (Rekkas & Wong, 2005). The preceding assumption for k endorses previous tourism literature on revisit intentions (Baloglu & Erickson, 1998; Gyte & Phelps, 1989; Oppermann, 2000b), which has contended that people tend to return to destinations they have visited before and that the intent to return decreases over time. Thus, the behavior of travelers over time is satisfactorily explained by using the Weibull probability distribution.

Simulation and Results

This section presents the results of a numerical simulation over 50 periods following the first visits to a destination to help demonstrate how visit flows through time might be determined by the pattern of repeat visits. To identify some of the fundamental influences at work, this simulation makes several simplifying assumptions, corresponding to those established in the previous section:

1) The destination attractiveness and marketing effort, the quality of the visitor experience it offers, and its competitive position remain constant throughout the 50 periods. This assumption permits us to abstract for the moment such affects as management action, although such factors are likely to influence repeat visit patterns (as well as on the initial visit M_j and return parameters λ and k). For our purposes, the destination's relative attractiveness, promotional effort, all other associated costs of a visit, and all other relevant prices are held fixed.

2) The initial populations, M_j, at the beginning of each period carry the same characteristics as previous periods, as individual characteristics are assumed to be unchanging. Moreover, the destination is allowed to gain or lose in terms of newcomers over the years, as Mj can remain constant.

3) Only (1-X) proportion of the M_j initial population that visited the destination, is likely to come back. X proportion drops out from the potential visitors' category as they release the destination from their choice set because of bad experiences or the visitors' being 1TO travelers.

4) Only one visit can be undertaken per time period per individual.

5) The probability of revisiting in any period t, for all individuals visiting at time j, is $Pr\{v_{t-j}\}$ given by a Weibull distribution; it decreases through time until T+j.

Figure 1: Repeat visits and their effect on visit flows: a three-period simulation

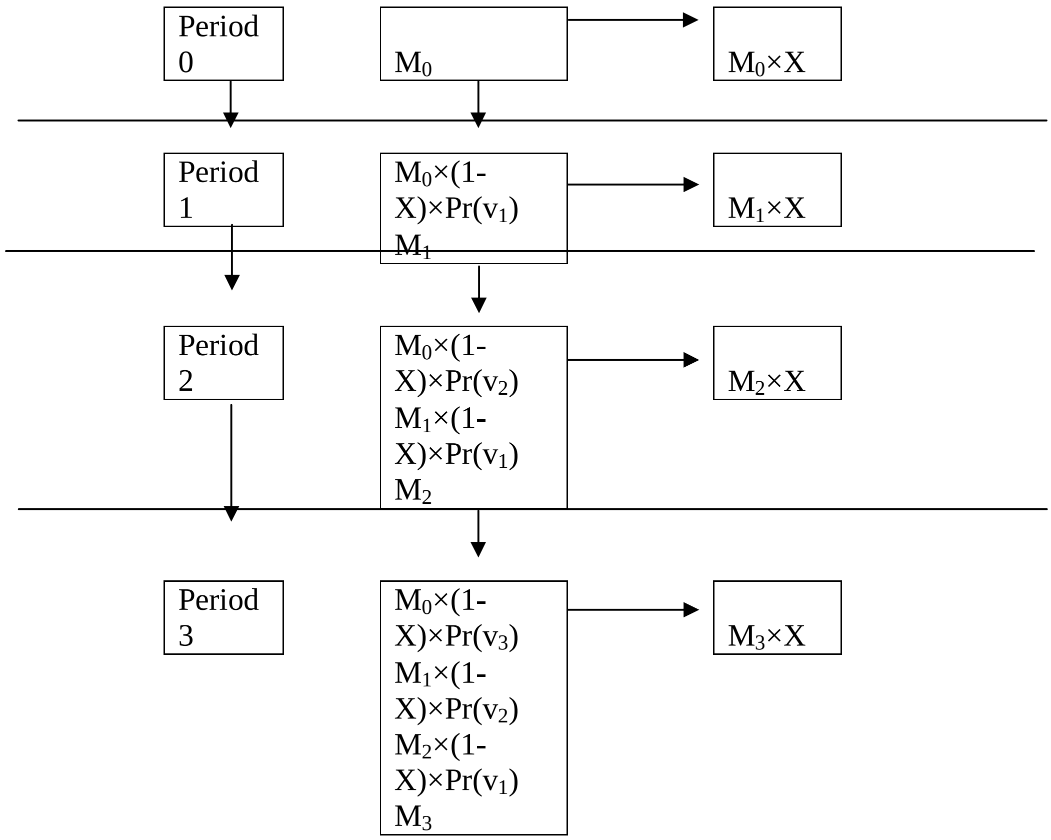


Fig. 1 uses these assumptions to show the derivation of visitor flows for the first three periods. It is clear that the effect of repeat visits on the visitor flow quickly becomes very complex; by the beginning of the fourth period (not shown), the population consists of the following groups:

(i) The number of individuals who initially visited the attraction at time 0, who didn't drop out and decided to return in time t=3.

(ii) The number of individuals who initially visited the attraction at time 1, who didn't drop out and decided to return in time t=3.

(iii) The number of individuals who visited the attraction for the first time at period 2, who didn't drop out and who decided to return in time t=3.

(iv) The cohort that entered at the beginning of period 3. These individuals are undertaking their first trip to the destination.

In the baseline simulation in Figure 2, the base values for M_0, λ, k, and T are given by the survey study, where:

(a) M_0=450; Growth=0%.

(b) λ=10 revisits on average every 20 periods; K=0.8 and T=20 years.

(c) X=10%, and is agreed on by previous literature on revisits (Darnell & Johnson, 2001).

In the baseline simulation illustrated in Figure 2, visitor numbers rise until period 20 and then stabilize. The initial rise is generated by the high pace and eminent probability of returns in early years (λ=10 and k=0.8), induced by new visits at times j. Period 20 represents the end of the cycle, T, after which revisits from period j are replaced by the most recent time revisits, and so on, keeping the number of revisits steady from this point onward.

Compared to the baseline simulation, Figure 3 applies different growth rates of initial visits. Two illustrations are used: 1) a growth case (2%) and 2) a decay case (-2%). In the first case, we see a permanent increase in visits over time. The effect of the growth in initial visits, though, is lower than the effect of revisits during the first 20 periods. This is reflected in the rising rate of increased visits subsequent to period 20. In the second case, an increase in the number of visits during early periods translates into a slight rate of decrease until period 20. Following period 20, the pace of decrease is higher, and the drop in initial visits is no longer sustained by repeat visits from previous periods. When the baseline, growth, and decay scenarios are combined on a single graph, the result mathematically proves Butler's (1980) theory on destination life cycle. The graph shown below (Figure 3) reflects all six phases Butler identified. Birth, involvement, and development are reflected in the growth path and correspond to growing number of new visits to the destination. Consolidation and stagnation are shown in the saturated path, which correspond to a stabilizing number of new visitors while relying more and more on repeat visits. Finally, decline on the decay path illustrates how the number of new and repeat visits drops sharply. Butler (1980) further argues that the cycle can begin again with a rejuvenation phase. This, however, requires a dramatic change in the resource base. Either a new set of attractions must be created or previously unexploited natural resources must be used. Realistically, changes to a destination anywhere between these two extremes is possible.

Figure 2: The time path of visitor numbers: baseline parameters profile

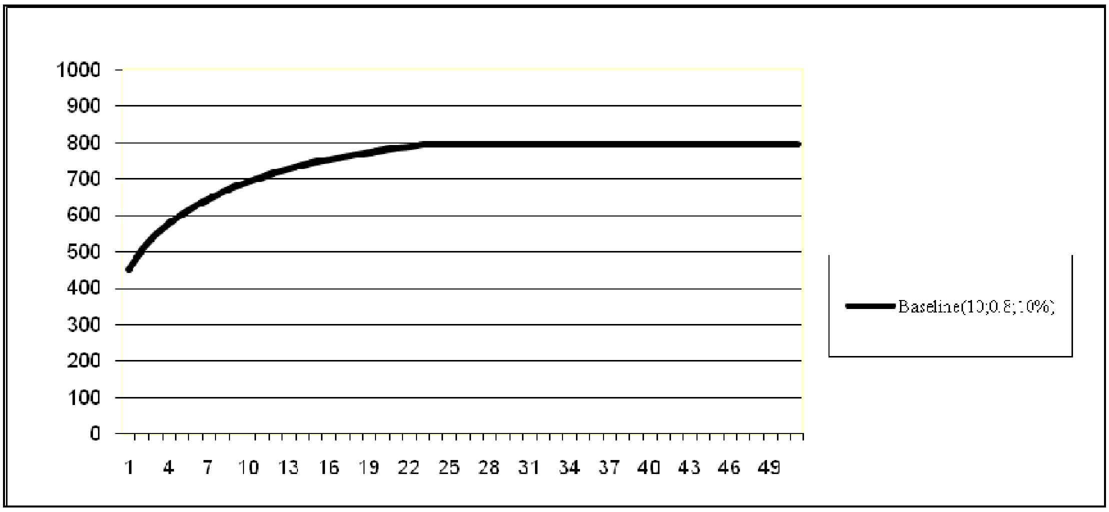
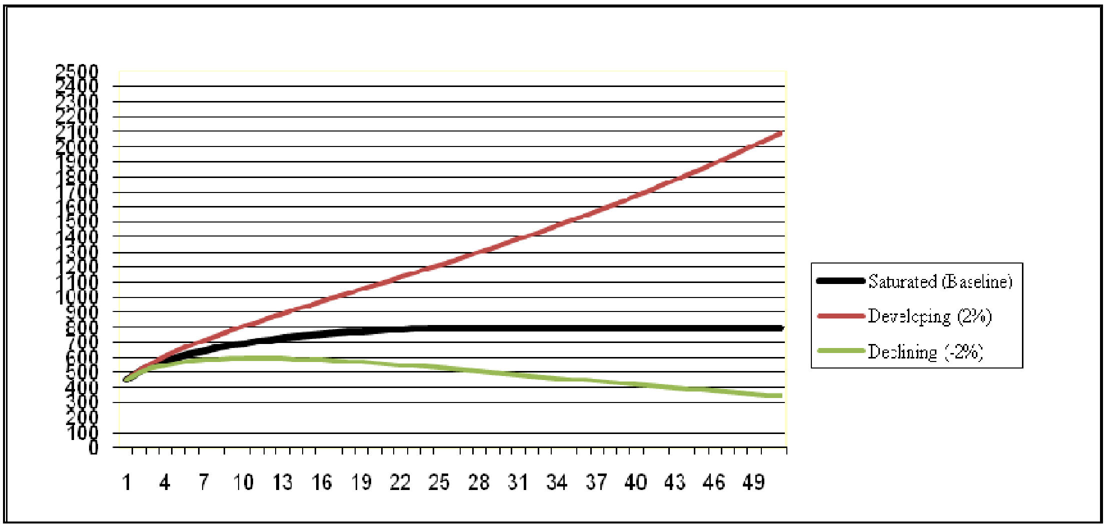


Figure 3: The time path of visitor numbers: growth and decay profiles



Compared to the baseline setting, Figure 4 varies k, or the shape parameter, of the distribution. The higher the k, the higher the probability of visitors returning in early periods. Subsequently, the higher the k, the shorter the time interval during which a repeat visit is likely to occur, and the faster the stabilizing level (in this example, 793 visits) is reached. The lower the k however, the more lengthy and lasting the return rate is, lasting past period 100 (which is difficult to show on this graph), until reaching the stabilizing stage of 793 visits.

Figure 5 applies different revisit averages to the 20 periods compared to the initial scenario. The higher the λ, or the average number of repeat visits over period T, the higher the early growth and the faster the stabilizing level of visits is reached. Thus, the more loyal or frequent the travelers (i.e., the higher the return rates, λ), the more they tend to come back (higher increase), and the more they keep returning.

Figure 4: The time path of visitor numbers: Different k parameters

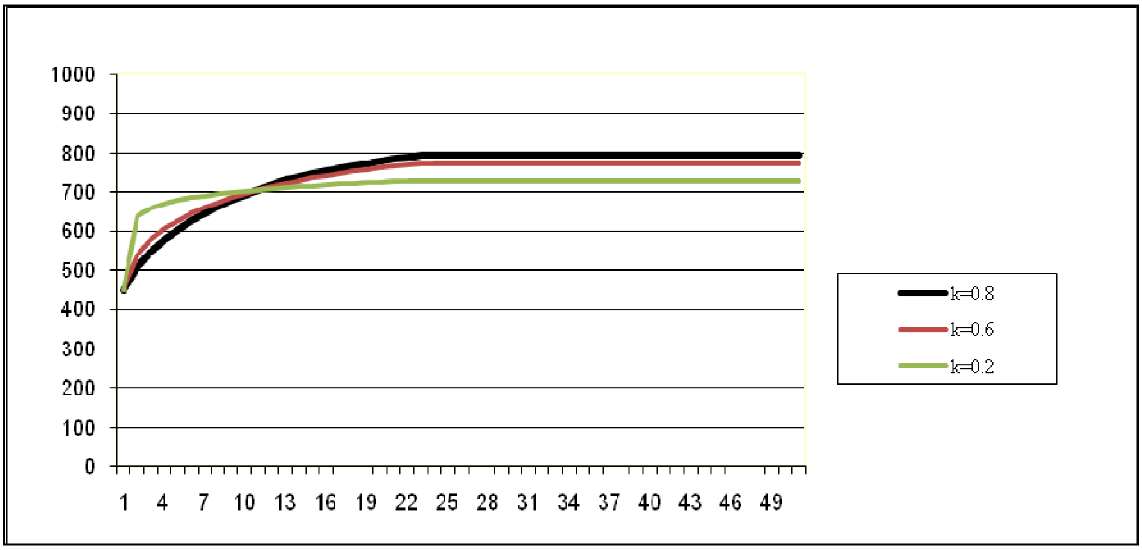


Figure 5: The time path of visitor numbers: different λ parameters**.**

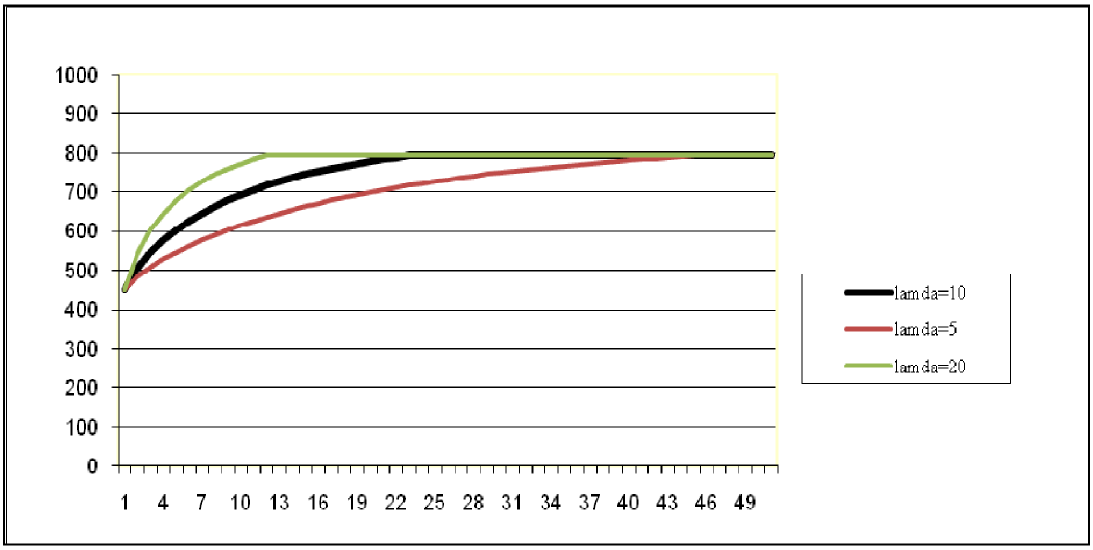


Figure 6 varies the drop-out rate of visitors from that illustrated in the initial scenario, where X=10%. Increasing X to 30% leads to a simple shift downward of the visits path, while keeping the same characteristics (increasing early trend and the same upper limit point T, corresponding to phase 20). This result can be explained by the fact that we did not alter the distribution parameters, λ and k.

Finally, to find the best way to stimulate visits to a destination, growth in initial visits, or growth in the number of returns over a given period, we again begin with the baseline scenario represented in Figure 7. In the first scenario, we implement a growth of 5% in period 5, which results in a shift up in the initial path starting period 6. This leads to a higher stabilizing level of visits over time. In the second scenario, we implement a growth of 5% in period 20, which results in a shift up in the initial path starting period 21. This also leads to a higher stabilizing level of visits over time (similar to the level reached in the first scenario). In the third scenario, we increase the return rate from 10 to 20 visits, which results in an increase in visits for early periods, after which we reach the same stabilizing level as the initial path, but less than the steady level reached in scenarios one and two. Thus, as we will discuss in the conclusion, it is better for the destination to boost new visits than to intensify repeat visits. This may be explained by the multiplying effect of new visits over time.

Figure 6: The time path of visitor number: different drop-out rates

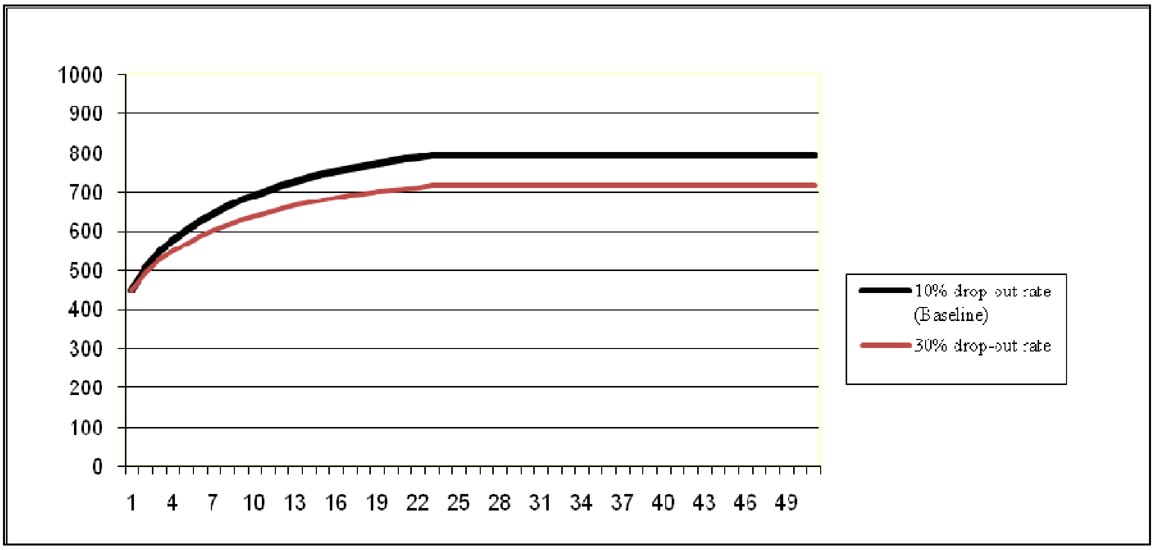
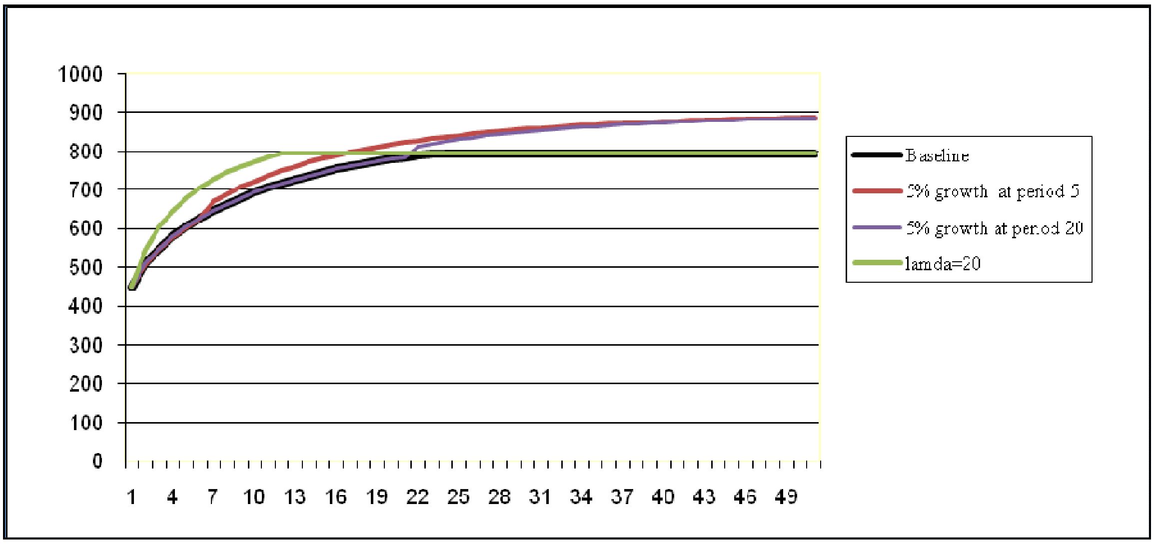


Figure 7: The time path of visitor numbers: different growth scenarios



Conclusion, Limitations, and Future Research

The schemas presented in this paper include further advances and fewer restrictions in pursuing a more realistic representation of repeat visits over time. Previous work on estimating return visits to a destination have been either conceptual and too simplistic (Darnell & Johnson, 2001) or have been limited to examining the dynamics between different events, such as a first-time visitor becoming a frequent, repeat visitor, rather than determining a way to estimate the number of revisits (and subsequently the total number of visits) to a destination at specific point in time (Baloglu & Erickson, 1998; Beaman, Kozak, & Huan, 2001; Taplin, 2003). In contrast, the present study provides a more pragmatic way to determine the level of repeat visits to a destination at a specific point in time and subsequently estimate the total flow of visits through time. Using tools such as the schema presented here could result in better data and better analysis for decision-making by destination managers.

Moreover, by considering the dynamics over time, the present study highlights relevant information for managing destinations, whether they are new destinations, have introduced a major new development, or those are well established.

First, the simulation scenarios help identify an appropriate time interval during which a purchase (in this case, travel) may or may not take place. In addition, by assuming visitors' characteristics are homogenous and an average rate of return per given period, and by incorporating the recency paradigm using an empirically supported Weibull function, the current study allows us to compute total visits during all time intervals induced by a first visit to a location.

Second, the simulations provide the important information that rapid early growth in saturated locations or those experiencing decay is temporary. In fact, an increase in initial visits, growth in the number of returns, or increase in return probabilities to a destination at any given period might have a long-lasting effect in terms of revisits (and subsequently the total level of visits) to that destination. This may have important implications for decisions about capacity.

Third, the time profile of repeat visits (i.e., distribution parameters), has important implications for visit flows. A key challenge for management is how they can influence that profile. Pricing, developing new attractions, and increasing marketing effort are ways to encourage repeat visit rates, but much will depend on the destination's objectives.

Most important, the number of first-time visitors and their dropout rates have the most significant and enduring impact on total visits over time because of the multiplying factor through time. First-time visitors are the most efficient tool that policy makers can use to boost travel to a destination (through promotions, marketing, and so on). Similar results were found in Darnell and Johnson's (2001) work. Despite their use of a constant return rate and regardless of revisit history, Darnell and Johnson (2001) stressed that increasing the entry rate (allowing the population to grow), visitor flows over time increase. This is explained by the fact that new visitors enter the population, and because of the model's assigned return probability, there is a greater chance that they will revisit (Darnell & Johnson, 2001).

On the other hand, simulations reported in the current study are based on some highly simplified assumptions. We have held all factors within the destination constant and have assumed that first-time travelers have homogeneous characteristics that match those of the newcomers exactly. Thus, the only element affecting the probability of making another visit is the time lag between the initial visit and the return visit to the destination. This limitation opens the door for further research.

Future investigation can build on this preliminary approach in several ways. First, future studies might focus on the relationship between the probability of visiting an attraction and the individual's characteristics, a relationship that could embrace demographic effects (e.g., whether some generations identify more closely with certain destinations than with others) and the impact of life-cycle circumstances (e.g., whether couples with children have a lower likelihood of revisiting). Previous empirical work has stressed the importance of household characteristics as main determinants of intent to return to a previously visited destination (e.g., Assaker, Esposito Vinzi, & O'Connor, 2011; Hsu & Kang, 2007; Sung, Marisson, Hong, & O'Leavy, 2001). Future extensions of the present study could incorporate these findings in terms of their effect on the probabilities of revisiting a destination. Doing so can help tourism marketers identify visitors with a higher probability of returning to the destination. Subsequently, valuable financial resources can be channeled toward potential consumers that are most likely to return to an area, while avoiding expenditures on those that will either definitely not visit the destination or have already decided to visit.

Future research could also examine the effects on visiting probabilities of factors over which attraction management can exercise some control. Not many of these factors exist, but they have been pointed out previously in the literature (e.g., Bigne, Sanchez, & Sanchez, 2001; Yoon & Uysal, 2005; Yuksel, 2001), including the destination's relative attractiveness (additional attractions, advertising and marketing, etc.), satisfaction levels with the stay at the destination, and associated costs of a visit that are within the destination's control (travel costs, lodging fares, certain subsistence costs, etc.). Again, knowing the sign and size of the impact of variables under management's control on return probabilities would be of great use for forecasting demand movements. Empirical work in this vein may be useful in suggesting the signs and size of such effects on the individual's (and hence a population's) probabilities of visiting a specific destination.

Quantitative modeling and estimation is another area in which progress can be made in studying non-repeat and repeat travelers. Arguably, a more perplexing combination of visitors can be introduced and modeled, such as frequent and less frequent travelers (Kozak et al., 2002), as can continuous repeaters, deferred repeaters, and continuous switchers (Feng & Jang, 2004). Each of these groups could have different revisiting probability distributions and different parameters, making the simulation more complex. Feng and Jang (2007) argued, however, that among the different categories of visitors, deferred repeaters are the most frequent and the group that should be emphasized to reinforce revisits to the destination. Thus, the present study sets the foundational bricks for understanding the effects of revisits on aggregate tourism flow to a specific location Much more, however, can be built on that foundation.

Another confounding issue is modeling multi-purpose trips. Generally, destination-choice models assume that travel is for vacations/pleasure and exclude business travel because it does not often indicate a destination choice (Oppermann, 1997). The real-world fact of mixing business with pleasure, however, or combining visits with friends/relatives with pleasure makes the issue of destination choice much more complex and so too the issue of destination revisits. Further research extensions could attempt to differentiate among such different categories using a more complex schema or model.

Finally, extensions of the current research could consider short-period cycles with seasonal influences, which could offer a more comprehensive approach for approximating the flow of visits through time. This would provide an additional step for removing seasonal obstacles in order to reach a more accurate approximation of total visits.

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