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The tourism area life cycle hypothesis: A micro-foundation

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Abstract
We provide a simple micro-foundation of the tourism area life cycle hypothesis, based on tourists' utility maximization. As a result of social interactions among tourists which determine destinations popularity, the market share of visitors which decides to visit a specific destination follows a logistic dynamics, consistent with what predicted by the tourism area life cycle hypothesis. We show that different preference drivers explain the duration of the different tourism area life cycle stages: the net benefit from visiting the destination characterizes the exploration, involvement, and development phases, while social effects associated with destination popularity characterize the phases of consolidation and stagnation Different from previous studies our results hold true independently of whether we focus on the repeating or non-repeating segment of the tourism market. We also provide a calibration of our model to the case of the city of Venice (Italy) showing that it performs well in capturing the evolution of tourism in the historical center of the city over the last 60 years, suggesting that TALC-like dynamics may occur even in the context of cultural and heritage destinations.

Keywords
tourism dynamics, tourism area life cycle, social interactions

Introduction

Tourism is an important means to favor economic development in several countries. Several studies, both from theoretical (Hazari and Sgro, 1995; Schubert et al., 2011; Marsiglio, 2015) and empirical (Lanza and Pigliaru, 2000; Lanza et al., 2003; Brau et al., 2007) points of view, document the central role played by tourism development in promoting economic growth and sustained improvements in standards of living, especially in small-island and developing countries. Understanding tourism

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patterns in order to predict tourist flows and accommodate them by eventually implementing appropriate measures is an essential task to effectively plan economic development. The tourism area life cycle (TALC) hypothesis proposed first by Butler (1980) is probably the most important theory discussed in literature in order to describe and predict the evolution of tourist numbers in a given tourism destination over time. Several extensions of the basic theory have been developed over the years, but in its simplest form the TALC claims that tourism destinations will experience different phases of economic, social and tourism development crucially affecting the number of visitors they may receive. Specifically, every tourism destination will tend to pass through five stages during which the number of tourists will increase more or less rapidly. During an early phase tourists will be very limited and mainly represented by explorers (exploration). Next, as information about the destination spreads and tourists increase, local residents will start to get involved by providing tourism facilities (involvement). In a following stage when information is already extensively spread through advertisement, campaigns and tourism facilities are extensive in place where tourist flows will keep growing regularly (development). Next, as advertisement campaigns become less and less effective and the supply of tourism facilities cannot be expanded further, the increase in tourist flows will gradually decrease (consolidation) till the point in which the peak of tourism will be achieved and the number of tourists will remain at a stable level (stagnation). Therefore, according to the TALC hypothesis the evolution of tourist numbers over time will follow a logistic pattern, as illustrated in Figure 1.

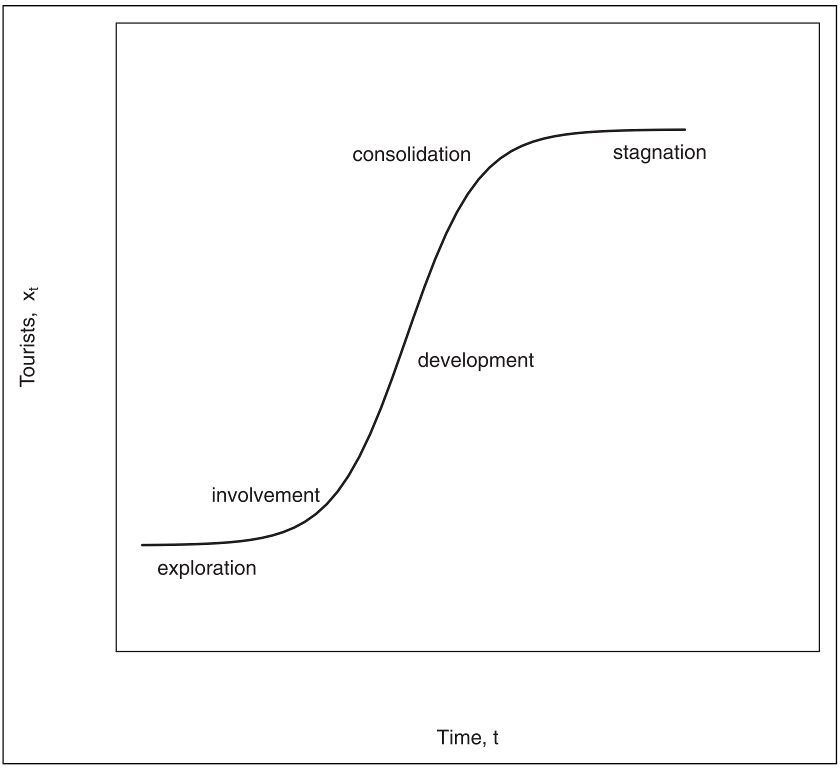

Figure 1. Tourism area life cycle hypothesis: predicted evolution of the number of tourists over time.

By relying on various methodological approaches, several studies analyze the different TALC phases from an empirical point of view (mainly in the context of sun-and-sun destinations) in order to assess the extent to which such a theory can effectively describe the experience of tourism destinations (see Butler, 2006a, 2006b). To the best of our knowledge, Lundtorp and Wanhill's (2001) is the only work trying to formally explain from a theoretical point of view why such a TALC dynamics may effectively arise. They develop a model of tourism market giving rise to a logistic differential equation describing the evolution of tourist flows; clearly its solution shows a pattern similar to what hypothesized by Butler (1980). However, despite the simplicity of their approach and its neat and intuitive results, their framework has two shortcomings: (i) the characterization of such a tourism market is entirely ad hoc and entirely based upon the exogenous diffusion of awareness and information about the specific destination abstracting completely from tourists' preferences and optimizing behavior, thus it is almost impossible to understand the determinants of tourism dynamics; (ii) moreover, they show that TALC-like dynamics can occur only whenever the tourism market is composed only by a repeating segment since as soon as a non-repeating segment is introduced in the analysis, the model becomes only a "*caricature of the real world*" (Lundtorp and Wanhill, 2001). Our goal is to contribute to this scant theoretical literature by providing an alternative and more rigorous explanation of why tourism destinations may experience TALC-like dynamics. Specifically, we build on Lundtorp and Wanhill's (2001) framework to provide a microfoundation of a tourism market based upon tourists' optimal destination choice and driven by social interactions. In our intuitive setting, independently of whether the market is composed by a repeating or a non-repeating segment, the evolution of tourists in the destination will show a logistic pattern, consistent with the TALC hypothesis. This suggests that the rationality underlying tourists' behavior ensures that TALC-like dynamics are the natural result of the social effects arising among tourists in response to destination popularity. We believe this result is particularly important as it shows that the TALC is not only a theoretical conjecture but a concrete possibility standing from tourists' rationality and optimal behavior. Moreover, by calibrating our model to the case of Venice (Italy), we show that it performs well in capturing the tourism evolution in the city over the last 60 years. We believe that also this result is quite important as, different from what it is commonly believed in literature (Garrod and Fyall, 2000; Russo, 2006), it suggests that TALC-like dynamics may occur even in the context of cultural and heritage destinations.

The paper proceeds as follows. *Non-Repeating Segment of Tourism Market* section introduces our baseline model which is a random utility framework in which travelers determine whether to visit a specific destination or not by taking into account both private factors (individually perceived benefits and costs) and social factors (popularity effects), including both deterministic and random elements. The decision of travelers to eventually visit the destination can occur only once, meaning that the model describes the behavior of only the non-repeating segment of the tourism market. We show that the share of tourists (relative to the size of the potential tourism market) effectively visiting a specific destination can be summarized by a differential equation, giving rise to a logistic dynamics. Since the size of the potential tourism market is constant, this means that the number of visitors a destination receives follows a pattern consistent with what hypothesized by the TALC hypothesis. This suggests that the optimal uncoordinated choices and actions of single utility-maximizer travelers at the aggregate level gives rise in a tourism destination to TALC-like dynamics, even in the absence of policymakers' efforts and attempts to affect tourism development. *Repeating Segment of Tourism Market* section proposes an extension of our baseline framework to allow for multiple visits, such that the model is able to characterize also the repeating segment of the tourism market; we show that also in this case our qualitative results do not change, suggesting that the TALC hypothesis is a natural result driven by the optimal decisions of single travelers partly driven by social interactions. Different from the baseline setup where in the long run all visitors will visit (only once) the destination, such an extended model allows for tourists to eventually repeat their visit multiple times and to characterize the carrying capacity of the tourism destination showing how such a maximal number of tourists that the destination is able to accommodate may be affected by specific policies. *Phases Estimation and Policy Insights* section shows how our analytical framework can be used to estimate when a destination will enter a specific phase predicted by the TALC theory and discusses the role of policy to escaping or postponing the entrance in the final stagnation phase. *Calibration* section presents a calibration of our model to describe the evolution of tourist numbers in Venice (Italy) in the 1960–2019 period, showing that our model captures well tourism dynamics in this context and that such dynamics are largely driven by social interactions. *Conclusion* section as usual presents concluding remarks and suggests directions for future research.

Non-repeating segment of tourism market

We consider a potential tourism market which is populated by a large number, N, of individuals indexed by $i = 1, \ldots, N$. For the sake of expositional simplicity, we shall refer to such individuals as "travelers." At any moment in time t, each traveler needs to choose whether to visit or not to visit a specific destination, say destination D. If the traveler decides to visit the destination, it will then become a "tourist" for the destination D. Thus, in the following we use the term traveler to denote an individual being part of the potential market, while the term tourist refers to a traveler who is actually visiting the destination. In making such a choice travelers try to maximize their utility by taking into account the benefits and the costs associated with their decision. Travelers are homogeneous in all respects but the perceived costs of visiting the destination, and such a cost heterogeneity reflects random shocks affecting individual ability to eventually visit the destination. We focus first on the non-repeating segment of the tourism market, that is each traveler will eventually choose to visit the destination only once; we shall remove this assumption in the next section showing that the results are qualitative identical.

Travelers are rational agents, driven by the pursuit of their self-interest, and thus they maximize their utility function which represents their preferences towards the two alternative options (visiting destination D or not) they face. As in random utility models (see Broke and Durlauf, 2001; Barucci and Tolotti, 2012) the utility function of each single traveler depends both on individual specific (including both homogeneous and heterogeneous factors) and social components. The benefit associated with visiting the destination is common to all travelers and is given by $b \geq 0$; this parameter captures the perceived attractiveness of the destination and includes all the potential (cultural, aesthetic, environmental, recreational) tourism drivers. The costs associated with visiting the destination are individual specific and stochastic; specifically, they are given by $c + \zeta_i$, where $c \geq 0$ is the deterministic cost common to all travelers while ζ_i is a random traveler-specific cost. The parameter c captures all those factors (time requirement, accommodation, and recreation costs) determining the cost of visiting the destination D which are to a large extent similar across all travelers, while ζ_i measures those random factors affecting the opportunity cost of visiting the destination (for example, the travel costs to reach the destination are to a large extent different from traveler to traveler according to geographical factors). Apart from such individual specific components, single travelers' choices are also affected by the behavior of other travelers which through a popularity effect tends to positively affect the utility of each single traveler. Formally, the decision of each single traveler to visit or not the destination is based on the following utility structure:

$$u_i(\omega_i) = \omega_i\big[b - (c + \zeta_i) + J\tilde{x}_i^e\big]. \tag{1}$$

If the traveler i does not visit the destination ($\omega_{i,t} = 0$) his utility is simply null, $u_i(0) = 0$. If the traveler visits the destination ($\omega_{i,t} = 1$) his utility is equal to $u_i(1) = [b - (c + \zeta_i) + J\tilde{x}_i^e]$, where the first two terms represent the private components of the utility while the third term is the social component related to the effect of other travelers' choices which determines a social externality. The impact of the social externality is equal to $J\tilde{x}_i^e$, where $J > 0$ determines the size of the externality effect (capturing the importance of social effects, and in particular popularity among travelers) and $\tilde{x}_i^e$ is the expectation of traveler i about the average of the choices of others travelers: $\tilde{x}_i^e = 1/(N-1)\mathbb{E}[\sum_{j\neq i}\omega_j]$. Travelers differ in their individual specific cost represented by the term ζ_i, where the random components of cost, ζ_i, $i = 1, \ldots, N$ are i.i.d. random shocks drawn from a common distribution η, which affect with different intensity the perceived cost of individual travelers. For the sake of simplicity, we assume that the shocks ζ_i are uniformly distributed over the unit interval. As a matter of expositional simplicity, we assume that the benefits from visiting the destination exceed the common costs component, that is $b > c$; if that is not the case ($b < c$) tourism in the destination will naturally tend to die out, which, for our purposes, is not interesting. We also assume that the common utility of visiting the destination is not too large and specifically it does not exceed one, that is $b - c + J < 1$; if this is not the case ($b - c + J > 1$) tourism development will be too fast and every traveler will visit the destination almost immediately, which is again not interesting for our goals. For these reasons, we shall focus on the most interesting situation in which parameters are such that $0 < b - c < 1 - J$, suggesting that the net benefit from visiting the destination is positive but not too large. The net benefit from visiting the destination, $b - c$, quantifies the magnitude of all those privatively perceived (beneficial net of detrimental) factors which might affect the individual decision of a single traveler to visit the destination, and as we shall see later this parameter plays an important role in our analysis.

It is possible to show that the utility formulation as in (1) turns into a probabilistic choice model, which as shown in the literature on social interactions (see Blume and Durlauf, 2003) can be recast into a dynamic probabilistic model. Define $x_t^N = 1/N\sum_{i=1}^N \omega_{i,t}$ as the fraction of travelers visiting the destination at time t; then x_t^N represents the number of tourists (relative to the size of the tourism market) actually visiting the destination D at time t. The dynamic probabilistic model can be summarized as follows: $\mathbb{P}(\omega_{i,t+\Delta t} = 1|\omega_{i,t} = 0, x_t^N) = \eta(b - c + Jx_t^N)$, where η represents the distribution function of the random factors ζ_i, $i = 1, \ldots, N$. This suggests that, at any point in time, a single traveler will become a tourist for destination D with a certain probability which increases in both $b - c$ and in Jx_t^N. Analyzing the dynamics involved in such a probabilistic model is particularly complicated, but it is possible to describe in closed-form the deterministic dynamics emerging from the asymptotic version of the model, derived by letting the number of travelers tend to infinity. Whenever we let $N \to \infty$, the dynamics of the share of travelers deciding to visit the destination, x_t, which thus represents the (relative) number of tourists the destination D receives at time t, can be described by the following differential equation:

$$\dot{x}_t = (1 - x_t)(b - c + Jx_t). \tag{2}$$

Equation (2) describes in a very simple form the evolution of the share of tourists (relative to the potential market) visiting the destination, given the initial value of tourists, x_0. Since the size of the potential market is constant, it also describes the evolution of the number of tourists visiting the destination. For all relevant parameter values (that is $0 < b - c < 1 - J$), it is straightforward to show that the unique stable equilibrium is represented by $\bar{x} = 1$, which means that over the long run all travelers will visit the destination once. Moreover, the equation above, independently of the initial condition x_0, describes a logistic-type differential equation, whose time dynamics shows an S-shaped pattern, exactly as suggested by the TALC hypothesis; this is illustrated in the left panel of Figure 2, where we set parameters as follows: $b = 0.0002$, $J = 0.3$, $c = 0$ and $x_0 = 0$. As the figure suggests, even if $x_0 = 0$ over time the number of tourists will rise, first slowly and then fast before slowing down again and converge toward a constant level, equal to the unity, in the long run. Note that such an S-shaped pattern in the evolution of tourist numbers in the tourism destination is derived from an equilibrium condition in the potential market, whose dynamics is endogenously determined by the optimal choices of single travelers. Different from what discussed in Lundtorp and Wanhill (2001), the evolution of tourist numbers is endogenous and shows a TALC-type behavior even if we focus only on the non-repeating segment of the tourism market.

According to the parameter values, and in particular to the size of the social externality and the relative size of benefits and costs associated with visiting the destination, the evolution of tourist numbers in the destination will tend to be faster or slower, and the different phases of the TALC will tend to be longer or shorter. The right panel in Figure 2 shows the tourist dynamics associated with different values of such parameters. In particular, we use the left-panel values ($J = 0.3$, $b = 0.0002$, $c = 0$) as a benchmark scenario represented by curve (a); the other four scenarios (b)–(e) present, respectively, higher/lower values for J/b. With respect to the benchmark, we can see that curve (b) has a higher value of J and thus a faster tourist growth, while curve (c) has a lower J and a slower growth. Similarly, curve (d) has a higher b and thus a faster tourist growth, while curve (e) has a lower b and a slower growth. Note that at some point, the curve (b) overpasses (d) thanks to the larger J, and something similar happens when comparing curves (c) and (e). In some sense, the net benefit $(b - c)$ is responsible for the starting portion of the curve (the exploration, involvement and development phases in the TALC perspective) while the social externality (J) for its second part (the phases of consolidation and stagnation). This analysis suggests that the development of the tourism destination will be slower when the costs for travelers are higher, their benefits are lower or the

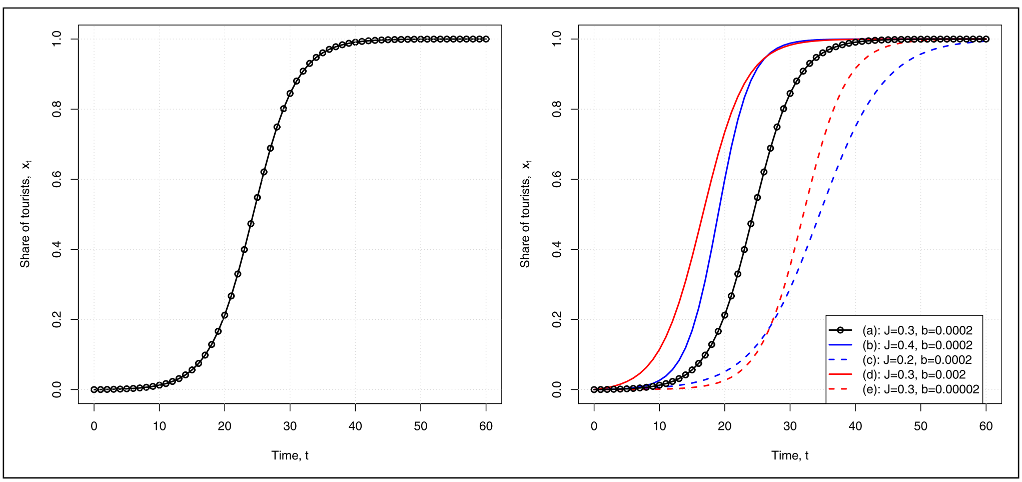

Figure 2. Time evolution of the share of tourists in the destination in the case of non-repeating visits. S-shaped pattern consistent with the tourism area life cycle hypothesis where $J = 0.3$, $b = 0.0002$, $c = 0$ and $x_0 = 0$ (left); effect of different policy changes (J and b) on the tourist dynamics (right).

social externality is weaker. This suggests that different policies (even social policies aiming to affect the popularity of a destination) can eventually be used to speed up the development of the destination but over the long they will not have any long-lasting effect; this is simply due to the fact that in the non-repeating segment of the tourism market, once all travelers have visited the destination nothing can be done to attract further (non-repeating) tourists.

Repeating segment of tourism market

We now consider a simple extension in order to allow for travelers to eventually visit the destination more than once, meaning that we now focus on the repeating segment of the tourism market. The probabilistic choice model is very similar to what discussed in the previous section, apart from the fact that upon completion of a visit travelers may choose to visit the destination again. This is captured by a parameter $\delta > 0$ which measures the depreciation of the utility generated by a visit (i.e. memories after a while fade away); as soon as the utility yielded from a tourist experience in the destination is entirely depreciated, travelers may choose to revisit the destination D. Briefly, the stochastic N-finite model is now characterized with two different probabilities: $\mathbb{P}(\omega_{i,t+\Delta t} = 1 | \omega_{i,t} = 0, x_t^N) = \eta(b - c + Jx_t^N)$, as before, and $\mathbb{P}(\omega_{i,t+\Delta t} = 0 | \omega_{i,t} = 1) = \delta$. Note that, δ represents mathematically the expected waiting time for a transition from state $\omega = 1$ to state $\omega = 0$, or, in other words, the expected waiting time for a new visit to potentially occur. As in the previous section, it is simpler to analyze the asymptotic population model, which we now focus on. The dynamics of the tourist number in the destination D is now determined by the following differential equation, which resembles (2) with a correction term depending on δ:

$$\dot{x}_t = (1 - x_t)(b - c + Jx_t) - \delta x_t. \tag{3}$$

The depreciation rate plays a crucial role in the above equation: if this is null we are back to the previous case in which revisits are not possible, while if this is strictly positive revisits will endogenously occur. As equation (2) in the previous section, also equation (3) is a quadratic differential equation which gives rise to a logistic-type dynamics, and thus is consistent with the TALC hypothesis (see Figure 3, which is obtained by setting parameter values as follows: $b = 0.0002$, $J = 0.3$, $c = 0$, $x_0 = 0$ and changing δ). This means that also in the repeating segment of the tourism market the TALC hypothesis summarizes well the evolution of tourists over time. However, different from what is discussed in the previous section, in this case, the unique stable equilibrium is critically determined by the specific values of the main parameters since this is no longer equal to unity but given by the following expression:

$$\bar{x} = \frac{J - (b - c + \delta) + \sqrt{[J - (b - c + \delta)]^2 + 4J(b - c)}}{2J} \in (0, 1) \tag{4}$$

It is straightforward to show that this is the only possible equilibrium within the relevant parameter range (i.e. $0 < b - c < 1 - J$). Since $\bar{x}$ as defined above is strictly smaller than unity, by focusing on the repeating segment of the tourism market, we can conclude that only a certain share of the potential market will be effectively visiting the destination in the long run, and such a share may be composed by both repeating and non-repeating visitors. Indeed, whether an individual traveler decides to visit the destination more than once depends on individual-specific characteristics and social effects, which determine the endogenous choice of each single traveler. The

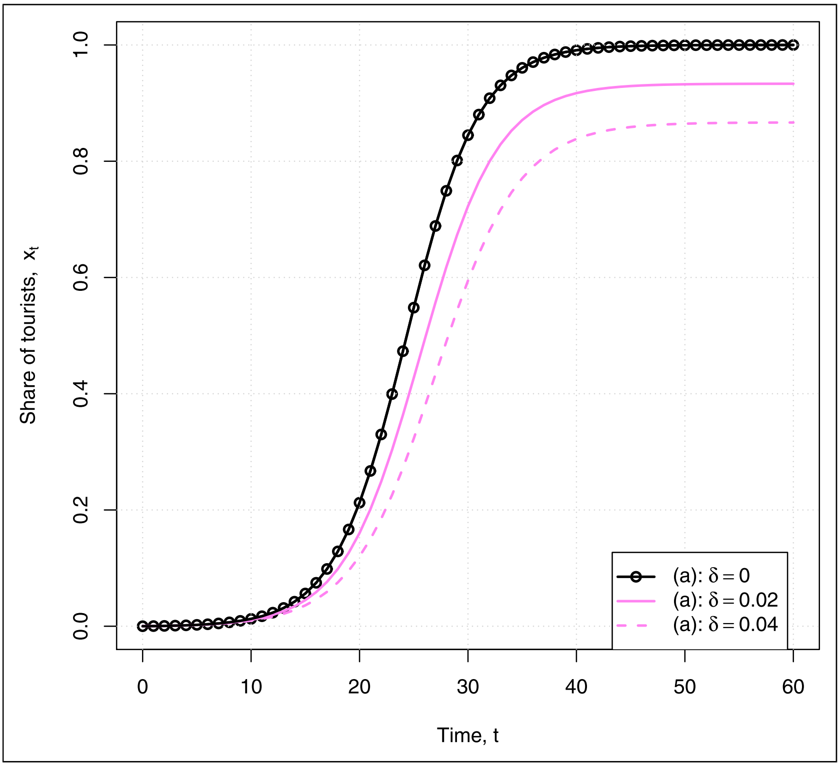

Figure 3. Time evolution of the share of tourists in the destination in the case of repeating visits. S-shaped pattern consistent with the tourism area life cycle hypothesis where J = 0.3, b = 0.0002, c = 0, x_0 = 0 and different values of δ.

equilibrium value in (4) suggests that the number of tourists in the long run will tend to stabilize to a level which is determined by four factors: the benefits b and the costs c of visiting the destination, the social externality J and the depreciation rate δ. Such a level represents what has been interpreted as the carrying capacity of the destination, that is, the maximal number of tourists a specific destination will be able to accommodate in the long run (Canestrelli and Costa, 1991; Marsiglio, 2017). In our setup, such a carrying capacity is expressed in terms of a share of the potential tourism market but, since the size of the market is constant, looking at shares and numbers is completely equivalent. The above analytical expression for the carrying capacity, which is derived endogenously as an equilibrium condition in the tourism market, allows us to understand how different policies might affect such a long run number of tourists. Indeed, the carrying capacity will fall with c and δ while it will rise with b and J. In this case, policies aimed at decreasing costs or the depreciation rate (i.e. by increasing the services associated with the tourism experience) but also those aimed at increasing benefits popularity effects will tend to increase the carrying capacity of the destination. Therefore, such policies will not have only transitional effects on the duration of the different phases of the TALC, as discussed in the previous section, but will also determine the peak number of tourists in the destination.

What discussed thus far implies that the evolution of tourist numbers in a given destination will tend to show an S-shaped pattern as suggested by the TALC hypothesis, and this is true both when the potential tourism market is composed by either a non-repeating or a repeating segment. It is possible to show that even extending the analysis to consider simultaneously the presence of non-repeating and repeating segments the results will not be qualitatively different and overall tourist numbers will show a logistic dynamics. This means that in its simplicity the TALC hypothesis captures well the patterns of development of tourism destinations since it is result of the aggregation of the optimal choices of a large number of individual travelers who compare benefits and costs in their tourism decisions. Clearly, the specific deterministic formulation with an infinitely large number of travelers that we have focused on thus far is only an approximation of the true random dynamics which may emerge in a real-world situation in which the number of potential travelers is finite. Despite the fact that closed-form solutions for such a framework are not available, it is however possible to show through numerical analysis that even in the finite number of travelers case, intuitively, the dynamics of tourists will still show an S-shaped trend but will also be affected by the randomness in the privately perceived costs which determine fluctuations in tourist numbers around such a trend. This is illustrated in Figure 4 where we plot the dynamics of the fraction of tourists, x_t, (blue curve) and one simulation of the finite-dimensional probabilistic model where $N = 1,000$ (red curve) in a specific model parametrization ($b = 0.0002$, $c = 0$, $J = 0.2$, $\delta = 0.04$). We can observe that apart from some quantitative difference, the dynamics of tourists predicted by the finite and infinite travelers models are qualitative identical and consistent with the S-shaped pattern hypothesized by the TALC. This comparison suggests that accounting for the eventual heterogeneity in the characteristics of travelers might be important to quantify the evolution of tourists, and

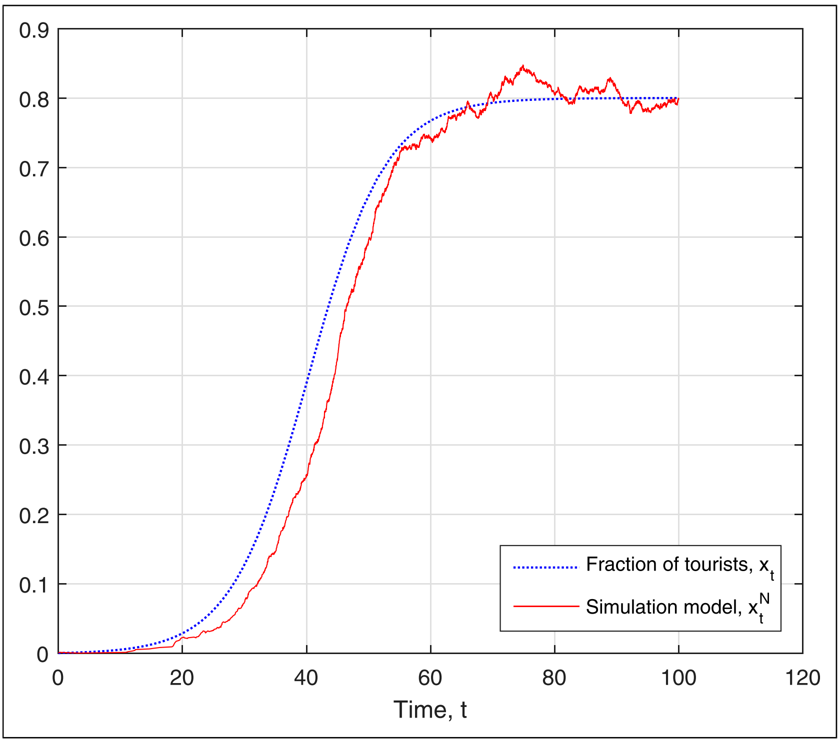

Figure 4. Time evolution of the share of tourists in the destination in the case of repeating visits, in a framework with an infinite (blue dotted curve) and a finite (red continuous curve) number of travelers.

such effects are actually captured by our dynamic probabilistic choice model, which however allows us to derive some analytical results only in its approximated asymptotic version.

Phases estimation and policy insights

Thus far, we have shown that the social interactions between utility maximizing tourists optimally determining whether visiting or not visiting a specific destination naturally give rise to a logistic evolution of the number of visitors in the destination consistent with the predictions of the TALC theory. Now, we try to move one step forward showing that our micro-founded economic framework allows also to predict when a destination will enter a specific phase of the TALC model (i.e., exploration, involvement, development, consolidation, stagnation) and thus to provide policy insights regarding how escaping or postponing the entrance in the undesirable final (i.e. stagnation) phase. Indeed, along the lines of Lundtorp and Wanhill (2001), we can identify the points where the logistic curve changes its concavity which in turn control when a destination enters a specific phase, given by the expressions below for x_i with $i = E, I, D, C, S$ where the different letters stand for the different TALC phases. Different from Lundtorp and Wanhill (2001), we determine such turning points establishing the role of specific parameters in driving the transition from one phase to the next. With some algebra, by calculating the points in which the third and fourth time derivatives (representing the characteristics in terms of monotonicity and curvature of acceleration) of the logistic curve are null, we can identify such five points:

$$\begin{aligned} x_E &= \frac{3(J-b+c-\delta)-\sqrt{6(J-b+c-\delta)^2+24J(b-c)}}{6J} \\ x_I &= \frac{3(J-b+c-\delta)-\sqrt{3(J-b+c-\delta)^2+12J(b-c)}}{6J} \\ x_D &= \frac{J-b+c-\delta}{2J} \\ x_C &= \frac{3(J-b+c-\delta)+\sqrt{3(J-b+c-\delta)^2+12J(b-c)}}{6J} \\ x_S &= \frac{3(J-b+c-\delta)+\sqrt{6(J-b+c-\delta)^2+24J(b-c)}}{6J} \end{aligned} \tag{5}$$

The expressions above identify the share of visitors required for a destination to enter a specific phase, and implicitly determine also the time in which such a phase will begin. Therefore, policymakers could in principle act in order to modify the perception of travelers (captured by the parameters δ, J, b, and c) in order to modify the aggregate dynamics anticipating or postponing the different TALC phases. Although a complete study of policymakers' efforts and attempts to affect tourism dynamics is out of the scope of this paper, we briefly present some policy conclusions.[1] First of all, note that (5) suggests that the starting point of involvement (x_E) is symmetric to that of stagnation (x_S) while the starting point of development (x_I) is symmetric to that of consolidation (x_C), where the symmetry is meant with respect to the starting point of development (i.e. x_D). This symmetry implies that it is not obvious to understand how affecting the tourism dynamics through policy interventions. Any attempt to postpone the entrance in a given phase requires to increase the starting point of that phase since the logistic curve is monotonically increasing over time, but this leads also to an anticipation of the entrance in some other phase (i.e., the starting point of some other phase decreases). Therefore, policies aiming to delay stagnation (consolidation) will result in anticipating exploration (involvement), suggesting that tourism policymakers need to carefully calibrate their policy interventions according to the specific phase experienced by the destination.

Since most concerns regarding the sustainability of tourism activities occur in a late phase of tourism development, let us forget about this issue and focus on the situation in which a specific destination is experiencing a consolidation phase and policymakers wish to delay (or even avoid) stagnation. This requires to increase x_S eventually to reach $x_S = 1$ in order to never end up in stagnation. The dependence of x_S on the net benefit from visiting the destination $b - c$ and the social externality J is ambiguous as it changes according to the parameter configuration, thus designing effective policies aiming to affect such parameters demands precise knowledge of the magnitude of the different drivers of travelers' preferences. The simplest and less information demanding approach consists thus of affecting the depreciation of the utility generated by a visit δ. Since x_S is decreasing in δ, interventions aiming at lowering δ (such as policies increasing the services associated with the tourism experience) will result in delaying stagnation. This result is consistent with what we have discussed in the previous section in relation to the carrying capacity and highlights the importance of the repeating segment of the tourism market in order delay or avoid stagnation.

Calibration

In order to understand to what extent our analytical framework is able to capture real world tourist dynamics, we now present a calibration based on the experience of Venice (Italy). Venice has historically been an important tourism destination thanks to its cultural and historical heritage but also thanks to its architectural design and scenic views. Over the last century the number of visitors in its the historic center has increased substantially, by a factor of four only in the last 60 years, putting under stress the entire urban area which due land and physical constraints is unable to expand its supply of tourism and leisure facilities without compromising the needs of local residents (Van der Borg et al., 1996; Russo, 2002). This has given rise to several episodes of tension between local residents and tourists over the last few years contributing to the steady depopulation experienced by the historic center (Zanini, 2017), such that nowadays understanding the dynamics of tourism and how to manage tourist flows in order to relieve tourism pressure and combat depopulation trends is a crucial priority for local policymakers in Venice (UNESCO, 2012).

Data on tourist dynamics in Venice are publicly provided by the Venice City Council and the Veneto Region (Cittá Di Venezia, 2010; Regione del Veneto, 2022), which disaggregate data at different districts level. We focus only on tourism in the historic center which is the area where most of tourism activities take place (Cittá Di Venezia, 2014), and we consider the 1960–2019 period to exclude the last few years in which tourism worldwide has been largely disrupted by the COVID-19 pandemic. In order to make these data consistent with our framework, we normalize them in terms of the number of visitors in 2019, and the evolution of such a normalized number of tourists staying in the historical center of Venice on a yearly basis is shown by the dotted points in Figure 5. This curve shows that the number of tourists in the city has not grown exponentially but has slowed down in the last decade such that the curve has begun to flatten out, which suggests as we shall clarify below that the final consolidation and stagnation phases have not been finally reached yet but if the trend continues they will be reached in the near future. Different from what it is commonly believed in literature, this confirms that the TALC hypothesis may be a valid theory to describe the tourism development in an important cultural and heritage destination such as the city of Venice.

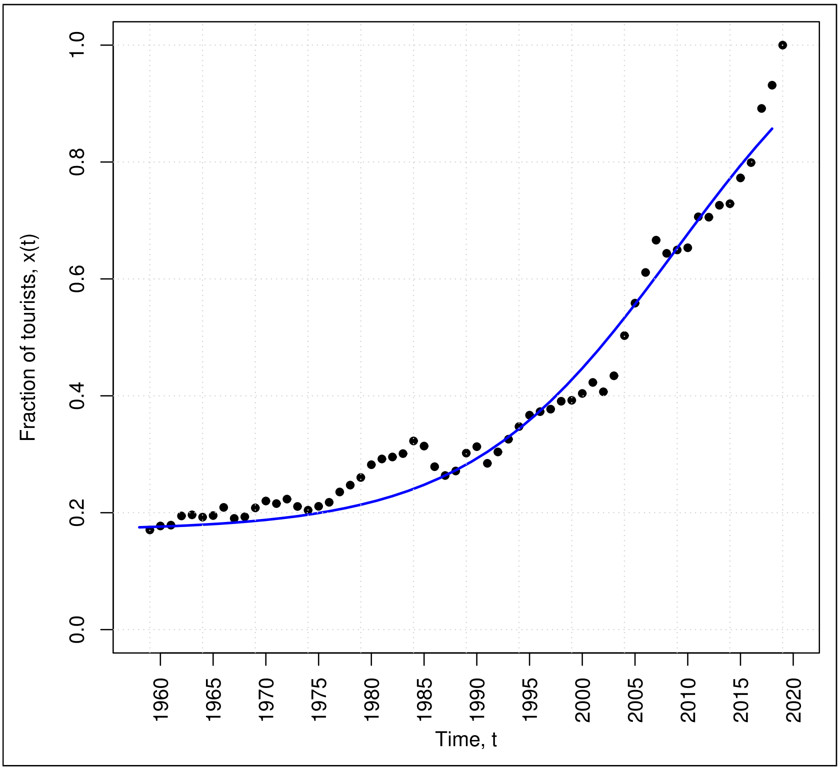

Figure 5. Time evolution of the share of tourists in Venice: real data (dotted points) and fitted data (blue curve).

We use our theoretical model to fit these data in order to understand how social effects and private incentives combine in determining such tourist dynamics. The curve best fitting this cloud of points based upon our infinite number of tourists model is represented by the blue curve, which clearly approximates well the data. Such a curve is based on the following parametrization: $b - c = 0.0006$, $J = 0.1060$, and $\delta = 0.005$, which satisfies our parametric restriction (i.e. $0 < b - c < 1 - J$) confirming that the data support the existence of TALC-like dynamics in Venice. Such a parametrization suggests that social effects captured by J are the largest component in individual travelers' utility and the net benefit h plays quite a marginal role, while the depreciation rate δ is one order of magnitude larger than the net benefit in individual travelers' preferences. Such a small value of the depreciation rate also indicates that the amount of time required for a tourist to revisit Venice is substantially large, suggesting that tourism in the city is predominantly dominated by non-repeating tourists. This result has important policy implications because it implies that in order to promote tourism development in the city it is crucial to design marketing strategies specifically tailored to first-timers. Moreover, by following the approach outlined in the previous section in order to estimate the starting point of the different TALC phases, our calibration suggests that Venice has entered the phases of exploration in 1986, involvement in 1996 and development in 2010, while those of consolidation and stagnation have not been reached yet and if the current (pre-COVID) trend continues they will be reached in 2024 and 2034, respectively. This imply that the city might need to accommodate over the next few years even more tourists that it is already doing, thus understanding how to manage the tensions between tourists and the local population is essential to favor the sustainability of the tourism industry in the city.

This calibration shows that our model of tourism market, driven by the optimal tourism decisions of travelers taking into account both social and private factors, mimics well the evolution of tourists in Venice over the 1960–2019 period. Despite the criticism that the TALC theory has received in the relation to its ability to describe the tourism evolution of cultural and heritage destinations and thus the limited number of empirical applications in this setting (Russo, 2006), our analysis suggests that TALC-like dynamics may occur even in the context of urban tourism and heritage cities in particular. Note that in the asymptotic formulation with an infinitely large number of travelers, it is possible to explicitly characterize the role played by private incentives and social externalities. Clearly, this is only a deterministic approximation of the true random tourism dynamics but it represents an important benchmark to better understand the future tourism prospects of real world destinations. The true random model with a finite number of travelers may be able to capture more closely the variability of real world tourism experiences and thus it can provide policymakers with deeper insights on the possible patterns of tourism development in specific destinations.

Some final remarks on our calibration exercise are needed at this point. Indeed, our calibration is based on a data fitting approach which is extremely useful to test the predictions of our theoretical model in the simplest possible form. With respect to other more sophisticated methods, this technique has the advantage of being not much data demanding as it requires only time series data on the number of tourists received by a given destination over a specific time period, but it has the drawback of neglecting the role of other important variables in determining tourism dynamics since these variables are all summarized in the key model parameters. Therefore, the empirical validation of our theoretical conclusions need to be taken with some grain of salt, but nevertheless we believe that our calibration is quite instructive in confirming the importance of tourists' optimizing behavior and social interactions among tourists in naturally giving rise to TALC-like dynamics.

Conclusion

The TALC hypothesis is one of the most important theory to describe the evolution of tourism, and specifically the evolution in tourist numbers, in a given destination over time. Such a theory has been extensively used both in qualitative and empirical analysis, but thus far a clear rationale for why tourism development should experience TALC-type dynamics has not been presented yet. The only exception is represented by the work of Lundtorp and Wanhill (2001), which describes how a tourism market may give rise to logistic dynamics, consistent with the TALC hypothesis. In this paper we refine their approach by providing a micro-foundation of this logistic tourism market: we show that the optimal behavior of individual travelers regarding their decision to visit or not to visit a specific destination ensures that at the aggregate level the tourism dynamics will be logistic. This is true both when we focus on the repeated and non-repeated segment of the tourism market, suggesting that overall the TALC hypothesis represents a good description of how tourist numbers might evolve over time in a given destination. We also characterize the role played by specific policies in affecting the duration of the different TALC stages along with the carrying capacity of the destination. We also show that our conceptualization of the tourism market represents well real world experiences, as demonstrated by our calibration on the basis of Venice's experience over the last 60 years. This calibration allows us also to show that social effects related to the popularity of a given destination represent an important determinant of travelers' utility and thus of tourism dynamics, and thus policies aiming to promote popularity among travelers (i.e., marketing policies increasing destination awareness and reputation) might make a significant difference in tourism development.

To the best of our knowledge, no other micro-foundation of the TALC hypothesis has ever been developed, thus we have tried to present our arguments in the simplest possible form. However, the analysis could be extended in order to distinguish the specific drivers of tourism choices of the repeating and non-repeating segment of the tourism market, or to take into account the diffusion of awareness and information regarding the specific destination through alternative communication means. This will not lead to results qualitatively different from ours, but it might be useful to better understand the possible role of alternative policies in determining tourist flows. Moreover, in our calibration exercise we have considered the specific case of Venice, which is a cultural city, typically attracting a particular type of tourists. It would thus be interesting also to assess the goodness of our theoretical model in the context of other destination types, such as sea-and-sand destinations. These tasks are left for future research.

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Notes

1. Similar to what discussed in Maggistro et al. (2022), it may be possible to analyze how results may change in the context in which policymakers maximize their utility by determining the optimal level of some parameter, such that their choice ultimately impacts the decisions of individual travelers at the aggregate level.

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