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Models of convex demand for quality

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Paving the way towards superstar destinations: Models of convex demand for quality

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Abstract

This article highlights the importance for urban planning, of the under-researched notion of superstar destinations. Furthermore, it presents and compares destination choice models that generate a convex demand for destination quality, and thereby explain and predict the existence of so-called superstar destinations. When compared to their competition, superstar destinations are much more popular than differences in quality between the superstar and other destinations would suggest at first sight. Although convexity of demand for quality is a known precondition for the existence of superstars, it remains unclear what mechanism might cause this imperfect substitution between different quality levels. The article proposes several choice models that generate a convexity of demand for quality, thereby paving the way for (modelling) the existence of superstar destinations. These models are compared using numerical simulations, which show that each of the proposed models has the potential to generate superstar effects, although for most models the effect decreases for larger choice sets. Results suggest that including reference-dependency into choice models helps overcome this potential limitation, as it leads to superstar effects for larger choice sets typically encountered in real life destination choice situations.

Keywords

Activity location, destination choice, travel behaviour, urban planning, transportation modelling

Introduction

The presence of so-called ‘superstars’ has been observed in a variety of forms, including artists (Schulze, 2003), songs (Salganik et al., 2006), movies (Elberse, 2008), football players (Lucifora and Simmons, 2003), Chief Executive Officer (CEOs) (Terviö, 2009) and museums (Frey, 1998). A common interpretation of the superstar phenomenon is that the difference in popularity between a superstar and its closest competitors (‘stars’) is much larger than their underlying differences in quality: even when the quality of the second-best alternative is only

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slightly less than that of the superstar, the difference in popularity is often found to be very large.

The superstar phenomenon is highly relevant for urban and spatial planners, as it helps explain demand for superstar destinations such as museums, football-stadiums, concert-halls and other attractions. For example the city of Amsterdam has been suffering from a severe over-concentration of tourism activity in and around its most famous museums (Rijksmuseum, Van Gogh museum), which causes high levels of inconvenience for visitors and inhabitants alike. In response, the municipality has for years been trying to divert visitors to other parts of the city, by opening and highlighting alternative attractions (Municipality of Amsterdam, 2011). The superstar effect helps explain why such efforts have so far been largely ineffective, as Amsterdam's superstar destinations continue to attract the large majority of visitors.

Interestingly, and despite the significant interest in the superstar topic in fields adjacent to travel and tourism research, the underlying reasons for the disproportional popularity of superstars (or: superstar destinations) are not yet properly understood. In the scholarly literature, the dominant explanation (Rosen, 1981) for the superstar phenomenon suggests that superstars emerge due to the combination of a convex demand for quality (i.e. as quality becomes higher, quality differences result in increasingly and disproportionately large differences in demand) and economies of scale in production output (i.e. production costs do not rise in proportion to demand). The main theoretical argument put forward to support the convexity of demand functions is that 'Lesser talent often is a poor substitute for greater talent... hearing a succession of mediocre singers does not add up to a single outstanding performance' (Rosen, 1981: 846). However, throughout the superstar literature, only little emphasis has been put on defining what exactly might cause this convexity in demand. Mainly for pragmatic reasons (Rosen, 1981: 847), it has been proposed that convexity may be assumed to be caused by a fixed cost of consumption per unit of quantity; this results in a competitive advantage for higher quality alternatives (resulting in convex demand) when consumers aim to minimize costs. However, it seems unlikely from a behavioural viewpoint that the convexity of demand for quality is purely or even mainly caused by decision makers' inclination to minimize consumption costs. Rather, it is to be expected that decision makers' tastes for quality itself play an important role in determining the shape of the demand function as well. In this context it is worth noting, that conventional specifications of discrete choice models (which is the category of models most likely to be used for the empirical investigation of superstar effects in contexts such as the destination choice situations described above) at first sight do not appear to generate superstar effects. On the contrary, these models generally predict that small differences in quality lead to proportional, hence small, differences in choice probabilities (i.e. demand).

This article contributes to the literature by putting forward several candidate specifications of destination choice models (of the Logit type) that do potentially generate a convex demand for quality and by implication superstar effects, without relying on the cost-minimization assumption mentioned above.

By doing so, the research presented in this article aims to contribute to the broader literature concerning (tourist) destination choices. A particularly influential stream of this literature focuses on the concept of 'destination competitiveness' (DC) of tourism destinations in particular; see Figure 1 in Botti and Peypoch (2013) which shows a rapidly increasing number of published studies on the topic. The DC literature has convincingly argued that DC is an often subtle function of a variety of different factors. Various DC models and operationalizations have been proposed over the years, differing in terms of which factors they include, and how these are combined into aggregate or over-arching DC

metrics. Although there has been considerable debate as to the proper way to conceptualize, operationalize and measure DC (Mazanec et al., 2007), there seems to be an over-all agreement that, next to conventional and objectively measurable concepts such as visitor numbers, also more subjective elements such as ‘quality of the tourism experience’ should be included to arrive at meaningful DC measures (Dwyer and Kim, 2003; Enright and Newton, 2004; Kozak and Rimmington, 1999; Zehrer et al., 2017). Strikingly, and notwithstanding the fact that the DC literature has produced a body of highly valuable and actionable results, the decision making processes of travellers themselves are rarely given centre stage in DC studies, as expert judgements (e.g. of tourism professionals) are typically used to construct and weigh different dimensions of DC measures (e.g. Botti and Peypoch, 2013; Crouch, 2010).

As such, the DC literature can be considered a complement to the discrete choice theory (DCT) based literature, which aims to develop and estimate tourists’ destination choice models based on revealed destination choices or choices made in experimental settings (e.g. Scarpa et al., 2007; van Cranenburgh et al., 2014; Wu et al., 2011). In contrast to typical DC studies, DCT research efforts focus on the traveller and her tastes (or: weights associated with the attributes of a destination), which in combination lead her to choose one (tourist) destination over another. These studies aim to empirically uncover these tastes in a process of econometric model estimation. What the two strands of literature (DC and DCT) have in common, is that they aim to understand how a variety of factors jointly determine the over-all attraction power of a destination, called ‘competitiveness’ in the DC literature, and typically ‘utility’ in the DCT literature.

The superstar modelling approaches put forward in this article take the outcome of the typical DC or DCT study as a starting point. That is, it is assumed that all destinations in a traveller’s choice set can be described in terms of an aggregate or over-all quality measure (which may be called destination ‘competitiveness’, or destination ‘utility’). The models take this aggregate measure (which may differ across travellers), and study how travellers translate it into an observable choice for a particular destination. In other words, the developed models aim to describe different decision rules that may be applied by travellers – each rule operating on an aggregate quality measure for each destination; it will be shown how different decision rules imply different types of superstar effects. As such, the present study complements, rather than aims to substitute, existing work in the DC and DCT strands of literature.

The remainder of this article is organized as follows: candidate models that generate superstar effects, are presented in the second section. This section also presents the outlines of an analytical framework (based on latent class (LC) analysis), which facilitates the empirical study of the conditions under which superstar effects are (un-)likely to be prevalent. The ability of the different model formulations to generate superstar effects is subsequently illustrated (tested) using a series of numerical analyses in third section. The fourth section provides conclusions and directions for further research. Note that as a secondary contribution, the article aims to bring the superstar effect to the attention of the spatial and urban planning field, where it has only received very little attention despite having clear scientific and policy relevance, and despite being an often used concept in related fields.

Candidate destination choice models and an analytical framework

Candidate destination choice models

A first candidate model postulates that the systematic utility of a destination is a simple linear specification of its quality: $V_i = \beta \cdot x_i$. Note that throughout the article, indexation for

individuals is omitted for reasons of readability. As in the remainder of the article, it is assumed that random errors are added which represent incomplete knowledge from the side of the analyst and are independently and identically distributed (i.i.d). Extreme Value Type I distributed with normalized variance equal to $\pi^2/6$. This leads to well known Logit probabilities (McFadden, 1973): $P_i = \frac{\exp(V_i)}{\sum_{j=1..J} \exp(V_j)}$. Crucially, in this candidate model, β is assumed to be (arbitrarily) large; this, given the normalized error variance, implies that destination choice behaviour is dominated by quality levels as opposed to other, unobserved factors. As a consequence, even small differences in (observed) quality are assigned much weight, which implies a potential for generating superstar effects. As an aside, note that in the limit (i.e. for very large β s) the model even becomes deterministic, in the sense that the superstar destination is assigned a probability of 1 even if it is only marginally better than the star, and all the others a probability of 0. This implies a winner-takes-all effect which can be considered an extreme case of a superstar effect.

A second candidate model assumes that destination utility is a convex function of quality: $V_i = (x_i)^\gamma$, with $\gamma > 1$. The assumption of a convex utility function would imply that as quality increases, an additional marginal increase in quality brings an increasingly higher amount of marginal utility. By implication, a convex utility function is expected to be able to generate superstar effects. It should be noted here however, that this assumption of convex utility implies risk taking behaviour in destination choices, which runs against the empirically well-established Weber–Fechner law (e.g., Masin et al., 2009) which postulates that for a difference in stimulus (in this case: destination quality) to be noticed, the difference must be *bigger* for bigger initial magnitudes of the stimulus (i.e. higher initial quality of the destinations).

The third candidate model is slightly less conventional than the two above mentioned ones, and hence will be discussed into more detail here. The model is reference-dependent, in the sense that it assumes that when evaluating a destination from a choice set featuring destinations with different quality levels, the decision maker uses quality levels of competing destinations as reference points. An implication of this assumption is that the model assumes that the anticipated satisfaction that is associated with a considered destination increases when the number of worse-performing alternatives (and the extent to which they perform worse) increases, and decreases when the number of better-performing alternatives (and the extent to which they perform better) increases. Especially in the context of entertainment-related behaviour (e.g., concert attendance, museum visits), which have traditionally been the main focus of superstar-related research and are particularly important from an urban planning perspective, the notion that comparisons with competing alternatives drives satisfaction seems an intuitive conceptualization of behaviour. Also note that the idea of reference dependent preferences builds on empirical evidence, accumulated in the field of applied economics over the years (e.g. Kivetz et al., 2004; Simonson, 1989), that decision makers – when considering an alternative – use quality levels of competing alternatives as reference points. Empirical evidence for the *additive* treatment in particular of reference dependent tastes can be found in Chorus et al. (2014).

Although a variety of (additive) reference dependent models is available, the focus is here on the most basic, generic type: in notation, $S_i = \sum_{j \neq i} (u(x_i) - u(x_j))$ gives the (systematic part of the) satisfaction which is perceived by the decision maker to be associated with a considered destination i , given perceived quality levels x_i and x_j for i and competing destinations j , respectively and the utilities u that are associated with the different quality levels (see further below for various assumptions that may be made concerning the shape of the utility function). Using the same error term assumptions as made above, choice probabilities are written in Logit form: $P_i = \frac{\exp(S_i)}{\sum_{j=1..J} \exp(S_j)}$.

To see how the proposed model predicts a convex transformation of destination quality to demand, consider an individual who faces a choice set of K destinations, ordered in terms of quality so that destination K has the highest perceived quality x_K , and destination 1 the lowest. For this moment, it is assumed for reasons of clarity of exposition that utility equals quality (in notation: $u(x_{in}) = x_{in}$). Assume that the quality of the superstar destination is only slightly higher than that of the (second-best) star. In notation, $x_K - x_{K-1} = \delta$, with δ being arbitrarily small. Given the model presented above, it is easily shown that the difference in satisfaction between the two destinations equals $K \cdot \delta$, which is a substantial amplification of the difference in quality, especially when the size (K) of the destination choice set increases. This satisfaction difference $K \cdot \delta$ consists of three parts: first, destination K generates a rejoice of magnitude δ due to the comparison with alternative destination $K - 1$; second, alternative K generates a rejoice associated with all bilateral comparisons with all the other $K - 2$ alternatives of lesser quality that is a magnitude δ larger than the rejoice generated by comparing alternative $K - 1$ with the same $K - 2$ alternatives; third, alternative $K - 1$ suffers a regret of magnitude δ due to the comparison with K . In combination, this implies that the small difference in quality between the star and superstar destinations is multiplied by K during the transformation from quality to satisfaction. When the choice set is sufficiently large, as is typically the case in destination choice situations, the amplification effect (i.e. $\delta \rightarrow K \cdot \delta$) results in large differences in satisfactions and resulting choice probabilities between the two stars, the superstar destination receiving very large demand at the expense of the popularity of the other competing destinations. An important implication of this third candidate model is that the superstar effect it generates becomes more pronounced as the choice set size increases (i.e. as K becomes larger). In other words: the model predicts that demand for quality becomes more convex, and the existence of superstar destinations becomes more likely, when destination choice sets are larger.

An analytical framework to study potential superstar effects on empirical data

Until now, the focus of this article has been on how to model superstar effects, under the implicit assumption that these are observed in real life – or, more to the point, in a given dataset under investigation of a researcher. However, there may be many situations where these effects are not present at all, or only in particular segments of the population, or in particular contexts. To impose a superstar model on data where superstar effects are not present, or where they are less prevalent than postulated by the model, would lead to suboptimal model performance in terms of estimation (parameter bias) and prediction (biased market share forecasts). An obvious but slightly ad hoc approach to deal with analyst uncertainty as to the prevalence of superstar effects in a particular situation (data set), would be to test different superstar models as well as regular, for example linear-in-parameter utility maximization models, based on the data. The remainder of this subsection presents a more subtle approach, which allows the analyst to study empirically which segments of the population are particularly prone to exhibit superstar effects, and which contextual factors may trigger such effects. The approach is based on the LC framework.

The LC framework (e.g. Vermunt and Magidson, 2003) is widely used throughout the Social Sciences, and is embedded in a variety of software packages (such as LatentGOLD and Limdep/NLOGIT). The framework allows the researcher to infer, from choice data, underlying sources of heterogeneity. In the domains of transportation and urban planning in particular, the framework is routinely used to model underlying heterogeneity in tastes

and in behavioural predispositions more generally (e.g. Greene and Hensher, 2003; Kroesen, 2014). Also in research efforts focussed specifically on modelling tourists' destination choices, the LC framework has been applied to infer taste heterogeneity across decision makers (Scarpa and Thiene, 2005; Scarpa et al., 2007; Wu et al., 2011). Before discussing how the LC framework may be used to model the absence or presence – or: different degrees of prevalence – of superstar effects in combination with the candidate models presented above, a very short outline of the framework will be presented first.

The LC framework is built on the assumption that the decision makers which make up the considered (sample of the) population of interest are heterogeneous in terms of their behaviour, but that they can be categorized in terms of a limited number of classes of individuals whose behaviour is relatively similar. What distinguishes the LC framework from more straightforward segmentation analyses which might for example explore different price sensitivities across income groups, is that the LC framework postulates that the classes of individuals with relatively homogenous behaviours are latent, that is not directly observable by the analyst. The LC framework consists of two parts: a class-specific choice model gives the probability that an individual, conditional on belonging to a particular class, chooses a particular choice alternative. This model predominantly includes attributes of choice alternatives as explanatory variables. A membership model gives the probability that an individual belongs to a particular class. This model may include socio-demographic attributes of the individual, and/or contextual factors, as explanatory variables. The combination of these two models gives the unconditional probability that a given individual, in a given context, chooses an alternative with a particular set of attributes. In notation: $P_{ni} = \sum_c [P_{i|c} \cdot P_{c|n}]$, where i denotes an alternative, n an individual and c a class. Furthermore, $P_{c|n}$ represents the probability that individual n is a member of a class c given her individual characteristics, and $P_{i|c}$ represents the probability that an individual who belongs to class c , chooses alternative i . Typically, both the class specific choice model and the membership model are specified as Logit models, although other model forms are possible. Traditionally, in the broader domain of planning as well as in the more specific area of destination choice modelling, the LC framework has been used to model taste heterogeneity. That is $P_{i|c}$ is only allowed to differ across classes in terms of the (estimated) tastes for attributes such as travel time and cost, destination quality and so forth. Crucially, the decision rule which translates these tastes into choices is typically postulated to be the same for each class, that is a linear in parameters utility maximization rule.

However, since recently transportation researchers have started to explore LC models where classes differ in terms of the decision rule itself, for example one class might be equipped with a conventional utility maximization rule, whereas another would be based on a regret minimization or elimination-by-aspects rule. While earlier work (e.g. Hess et al., 2012) focussed on identifying such latent decision rule heterogeneity in itself, later studies (e.g. Boeri et al., 2014; Hess and Chorus, 2015; Hess and Stathopoulos, 2013) have attempted to parameterize class membership functions in an attempt to explore determinants of decision rule heterogeneity. Resulting models have been observed to perform very well empirically (Chorus, 2014), suggesting that decision rule heterogeneity is an important factor underlying observed choice behaviour.

It is this particular specification of the LC framework which looks promising as a methodological tool to explore superstar effects while allowing for (i) the possibility that no such effects are in fact present in the data, and for (ii) possible differences in the prevalence of such effects, across different individuals and choice contexts. This is done by

equipping one or more classes with the superstar models presented in the previous subsection, while equipping other classes with conventional models that do not exhibit superstar effects. In the first place, such LC models will be able to infer, from observed choices, the share of individuals whose behaviour is consistent with that of a model which postulates the presence of superstar effects (based on a simple inspection of membership probabilities for the different classes). Secondly, when membership functions are appropriately specified, these models are able to identify which observable factors influence the probability that an individuals' behaviour may or may not exhibit superstar effects. These factors may relate to individual characteristics including socio demographic factors as well as, for example familiarity with the destination; and to characteristics of the choice situation such as the number and type of destinations.

Having specified the different candidate models and having explored how they may be integrated into an over-arching LC framework which includes non-superstar models, the next section numerically illustrates and tests in what ways and to what extent the different candidate models generate superstar effects.

Numerical illustration of how the different candidate models generate superstar effects

To illustrate (and: test) how the three candidate destination choice models generate convex demand for quality (and hence predict the existence of superstar destinations), a numerical Monte Carlo experiment is performed. Settings are as follows: a choice set of size K is created; alternative destinations numbered $k = 1..K - 2$ have an associated quality level x_k , drawn from a uniform distribution between 0 and 0.99. Note that similar analyses (not presented here, to avoid repetition) using normally distributed quality levels gave the same results. Which statistical distribution (uniform, normal, or another distribution) is most likely to resemble actual quality distributions across destinations is likely to differ per context, and remains in the end an empirical question. Nonetheless, the fact that results were found to be very similar for the uniform and normal distributions, can be considered a sign of robustness of the settings of the adopted numerical example, and of the behavioural model. Destination $K - 1$ (the second-best star) is assigned a quality level of 0.99, and alternative K (the superstar) is assigned a quality level of 1. Using these settings and by applying the models presented above, it is illustrated below how this very small difference in quality between these two best destinations may lead to potentially large differences in popularity, in the context of the three candidate models.

More specifically, each destination's choice probability is computed using each of the three models presented above. These choice probabilities are then multiplied by 10^6 to arrive at a measure of expected demand per destination from a hypothetical population of 1 million visitors. Subsequently, the expected demand for the star and superstar destinations is identified. Acknowledging that there is randomness in assigned quality-levels, this process is repeated 100 times and the average expected demand of the two star destinations – and the difference in demand between the two – is plotted as a function of destination choice set size (K), which is varied from 10 to 100.

Clearly, this set-up of the numerical experiment is a significant simplification of real life destination choice situations in various ways. Furthermore, exact outcomes are highly dependent on the specific values chosen above. Nonetheless, as will become clear below, the experiment does allow the inference of preliminary conclusions related to the ability of the different candidate destination choice models to generate superstar effects.

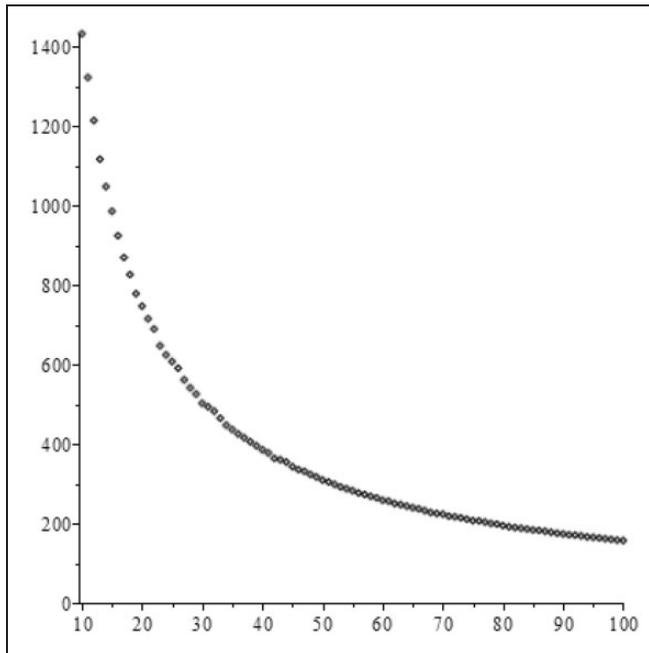


Figure 1. Difference in demand between superstar and star as a function of choice set size. Benchmark model: $V_i = x_{in}$.

As a reference case, we first explore a choice model where $V_i = x_i$, that is where utility equals quality. Figure 1 shows that, as expected for this base-model, no superstar effect emerges. Note that for reasons of succinctness, only the difference in demand between superstar and star is presented for the base case. The very small quality difference between star and superstar destinations translates into a very small difference in demand between the two destinations. Furthermore, as the choice set size increases, this already small demand difference in favour of the superstar destination gradually vanishes due to increased competition from newly added alternative destinations.

However, the expectation is that candidate model 1 ($V_i = \beta \cdot x_i$, with β sufficiently large), does cause superstar effects by giving much weight to (even small) quality differences. This expectation is tested by taking $\beta = 25$ in the context of the numerical experiment. For relatively small choice sets, Figure 2 indeed seems to suggest that the model $V_i = 25 \cdot x_i$ generates superstar effects, as the difference between demands for the two star destinations is substantial.

However, as was the case for the base model ($V_i = x_{in}$), the difference in demand between the two star destinations diminishes as the choice set gets larger: the added alternative destinations provide additional competition, eating away market share from both star destinations proportionally and as such reducing the difference in demand. This implication appears to be at odds with the notion that previous studies have without exception identified superstars in contexts where there are great numbers of alternatives to choose from (see the references cited in the introduction). And note that typically, destination choice set sizes are very large by nature. See also Elbers (2008) who finds – in the context of music and movie downloads – that as the choice set increases, the concentration of demand among a few superstars increases as well. As she puts it, the tail of the distribution ‘lengthens but flattens’.

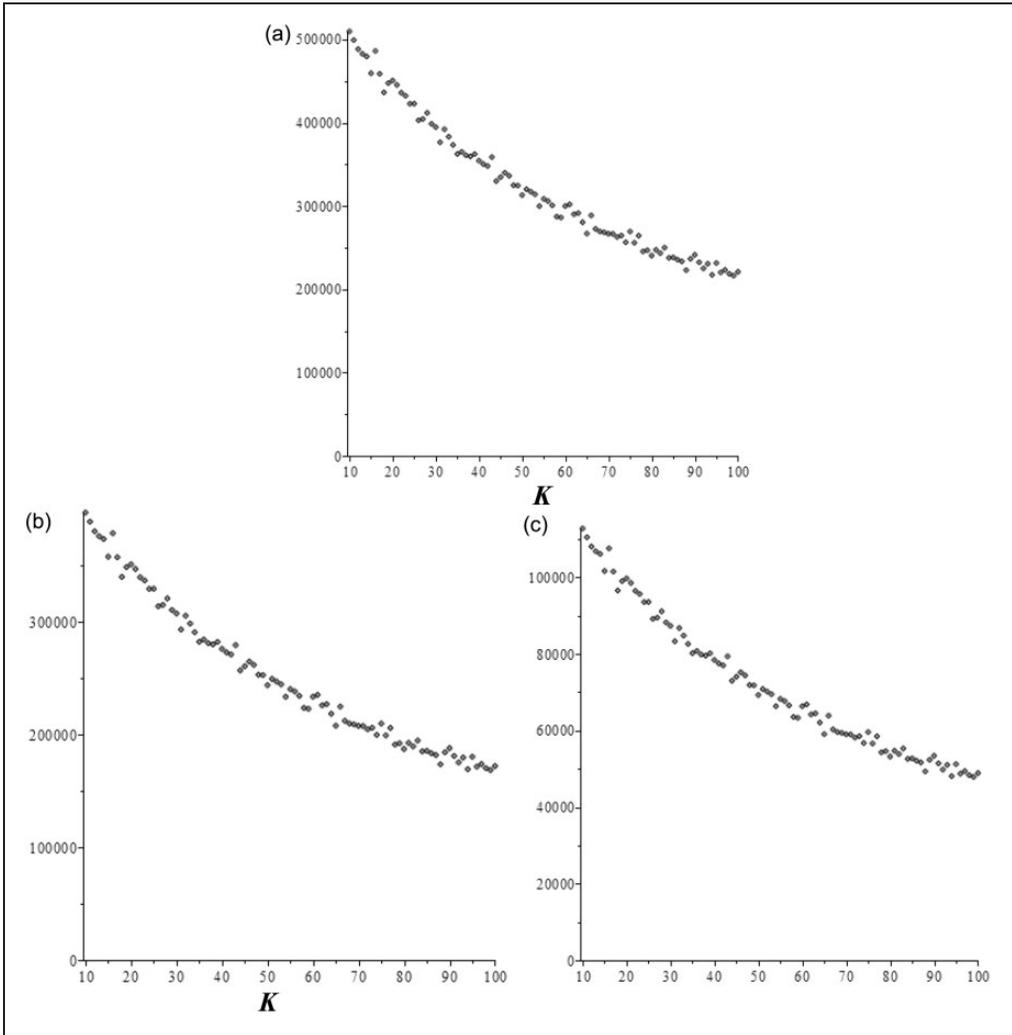


Figure 2. (a) Demand for the superstar destination as a function of choice set size for Model I: $V_i = 25 * x_{in}$. (b) Demand for the (second-best) star destination as a function of choice set size for Model I: $V_i = 25 * x_{in}$. (c) Difference in demand between superstar and star as a function of choice set size for Model I: $V_i = 25 * x_{in}$.

In order for this linear model to predict superstar effects for large choice sets, an extreme sensitivity for destination quality has to be present – whether or not this is realistic, of course remains an empirical question. It should be noted here, that, due to the IIA-property of the MNL model (which is due to the assumption of i.i.d. error terms), the *ratio* of demand between superstar and star destinations is not affected by adding alternative destinations to the choice set, as opposed the *difference* in demand. More specifically, in this particular simulation the ratio can be analytically shown to equal $\exp(25 - 25 \cdot 0.99) = 1.28$ in favour of demand for the superstar destination. However, the ratio of demand clearly seems to be a less intuitive and much less policy relevant metric of superstar effects than the difference in demand, especially when demand for

the two stars becomes small as is the case (in the context of the linear model) for large destination choice sets.

Candidate model 2 is expected to generate convex demand for quality, and the implied superstar effect, by means of a convex utility function $V_i = (x_i)^\gamma$, with $\gamma > 1$. This expectation is tested by taking $\gamma = 100$ in the context of the numerical experiment. This suggests an extreme case of convex utility, where only values very close to 1 are assigned a noticeable amount of utility. For relatively small destination choice sets, Figure 3 indeed seems to suggest that the model $V_i = (x_i)^{100}$ generates superstar effects, as the difference between demand for the two star destinations is substantial. Given that the utilities of the $K - 2$ worst performing destinations are all very close to zero, this demand difference can be closely approximated by the function $(\exp(1) - \exp(0.99^{100})) / (\exp(1) + \exp(0.99^{100}) + K - 2)$, which clearly is decreasing with choice set size and is not affected by simulation noise (hence the smooth plot in Figure 3). Note that, for reasons of succinctness, only a plot of the difference in demand for the two destinations is provided.

However, as was the case for the base model ($V_i = x_m$) and candidate model 1 ($V_i = 25 * x_m$), the difference in demand between the two star destinations diminishes as the destination choice set gets larger as the added destinations provide additional competition, eating away market share from both star destinations proportionally and as such reducing the difference in demand. In order for this convex model to predict superstar effects for large choice sets, an extreme degree of convexity has to be present – again, whether or not this is realistic, of course remains an empirical question. As was the case for the linear model, the *ratio* of demand between superstar and star is not affected by adding other destinations to the choice set; in this particular simulation the ratio equals $\exp(1 - 0.99^{100}) = 1.89$ in favour of demand for the superstar destination.

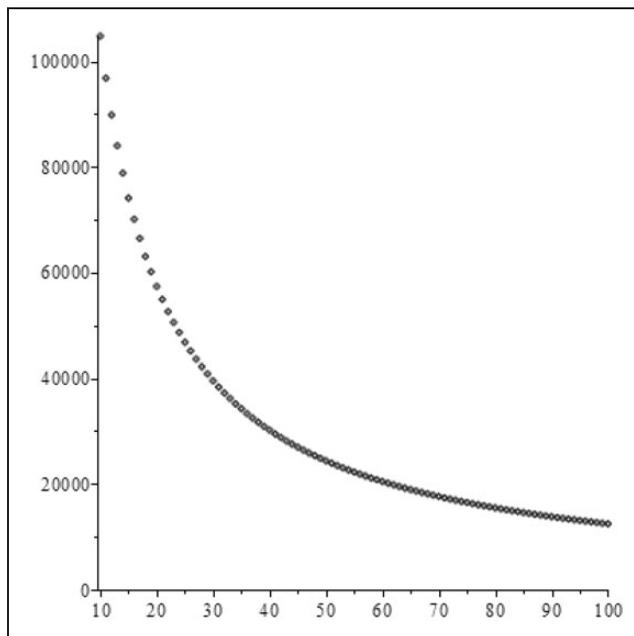


Figure 3. Difference in demand between superstar and star as a function of choice set size for Model 2: $V_i = (x_i)^{100}$.

Candidate model 3 aims to generate superstar effects by means of a reference dependent model of decision-making; each alternative destination is compared with every competing destination in terms of their quality. The resulting patterns presented in Figure 4(a) to (c) are unambiguous: when the choice set contains only 10 alternatives, the very small difference in quality already results in a noticeable difference in demand in favour of the superstar destination.

Interestingly, and in contrast with the linear and convex candidate models: when the number of destinations in the choice sets increases, the small quality difference between the two star destinations results in increasingly *large* differences in terms of demand as the

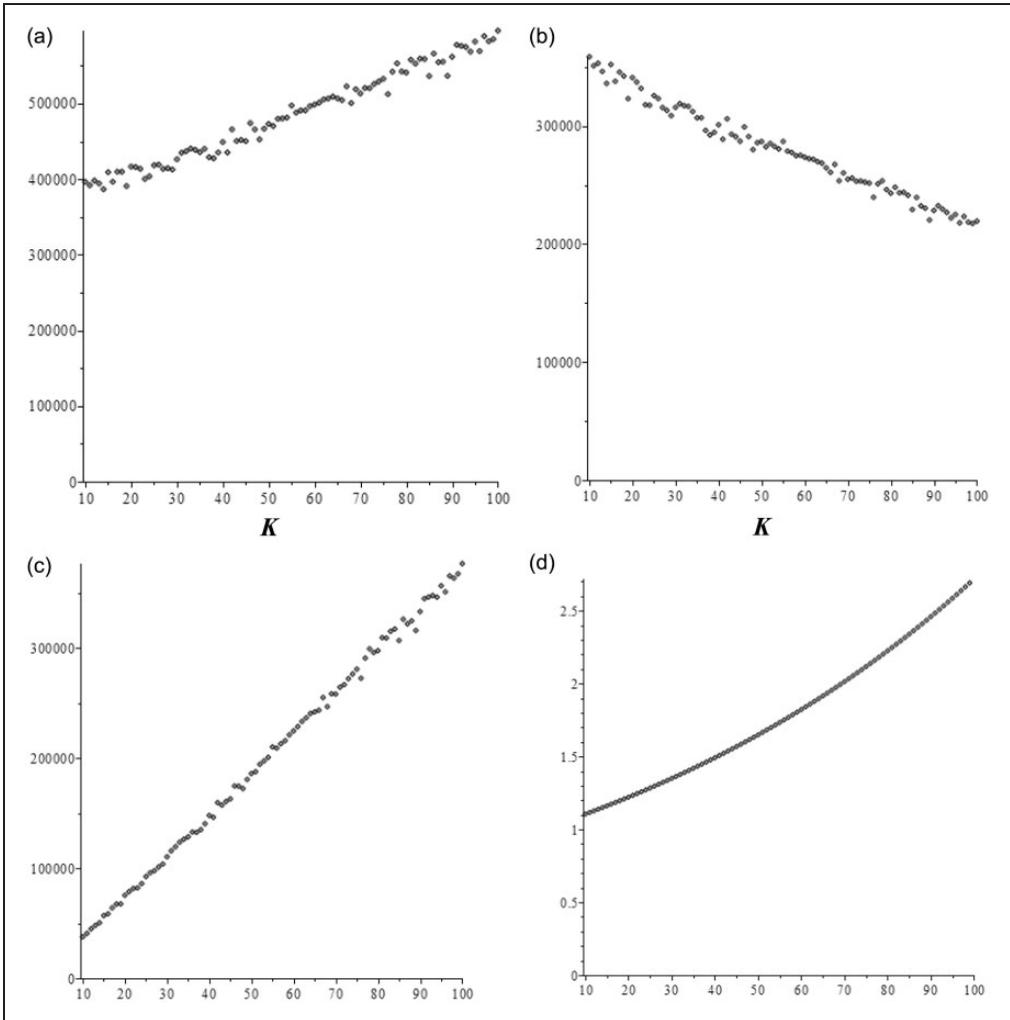


Figure 4. (a) Demand for the superstar destination as a function of choice set size for Model 3: $S_i = \sum_{j \neq i} (u(x_i) - u(x_j))$. (b) Demand for the star destination as a function of choice set size for Model 3: $S_i = \sum_{j \neq i} (u(x_i) - u(x_j))$. (c) Difference in demand between superstar and star as a function of choice set size for Model 3: $S_i = \sum_{j \neq i} (u(x_i) - u(x_j))$. (d) Ratio in demand between superstar and star as a function of choice set size for Model 3: $S_i = \sum_{j \neq i} (u(x_i) - u(x_j))$.

absolute demand for the superstar destination increases and that for the second-best or star destination decreases. In other words, the addition of relatively low-quality alternative destinations to the choice set leads to an increase in demand for the highest quality alternative in the set, which reflects the notion that the demand-bonus associated with being the highest-quality destination in the choice set increases as the choice set gets larger (see Candidate destination choice models and an analytical framework section).

This is also reflected in the result (Figure 4(d)) that rather than staying constant, the ratio of demands for superstar and star destinations increases as the choice set grows: due to its reference dependency, model 3 does not exhibit the IIA property (which postulates that the ratio of demand for two alternatives is unaffected by the absence/presence of other alternatives) even though its errors are i.i.d. The ratio of demands for this model in the context of this particular simulation equals $\exp(K \cdot 0.01)$, which increases with choice set size and is not affected by simulation noise. For example for a choice set of size 100, the ratio equals euler's number (≈ 2.72). In sum, candidate model 3 generates superstar effects in terms of the difference as well as the ratio of demand for destinations.

Where candidate models 1 (linear) and 2 (convex) were criticized from behavioural viewpoints such as their reliance on an extreme sensitivity to quality changes, or an extremely convex utility function (which contrasts with Weber's law), the reference dependent model can be subject to another behavioural criticism. More specifically, it seems hardly realistic to assume that individuals making a destination choice have the cognitive capacity or the wish to perform the elaborate inter-alternative comparisons that lie at the root of the proposed decision-making model. This criticism would seem even more justified when the choice set is very large, as is typically the case in destination choice contexts.

Nonetheless, it can be shown that the reference dependent model of destination choice behaviour also generates superstar effects when it relies on a relatively small number of inter-alternative comparisons. More specifically, as will be illustrated numerically below, it turns out that as long as a (fixed) fraction of the number of destinations is used as reference points, the reference dependent model still generates superstar effects which grow larger as the destination choice set size grows. To illustrate this phenomenon, Figures 5 and 6 show the demand differences (panel a) and ratios¹ (panel b) for a reference dependent model in which only one in four (Figure 5), respectively one in eight (Figure 6) destinations is subjected to a comparison with a considered destination. This latter variant thus assumes that in case of a choice set with, for example around² 80 destinations, 10 destinations are used as a reference point. Note that analyses not reported here show that it does not matter if the star and superstar destinations themselves are always included or always excluded as reference points for the evaluation of other destinations. Figures 5 and 6 are based on the assumption that the two star destinations are always including in the subset of destinations used as reference points. These figures clearly show the same trend as provided in Figure 4, for the model which is based on the behaviourally less realistic assumption that every single competing destination is subjected to a comparison with a considered destination. As expected, the superstar effect becomes less pronounced though, as less competing destination is used in the evaluation process.

Importantly, intuition as well as simulation results not reported here (for reasons of succinctness) suggest that in order for the reference dependent model to generate superstar effects, the size of the subset used as reference points needs to grow with the size of the full choice set. This is for example the case when, as in the simulations reported directly above, a fixed *fraction* of alternatives is assumed to be used as reference points. However, when, say, a fixed number of destinations (e.g. 10) is used as reference

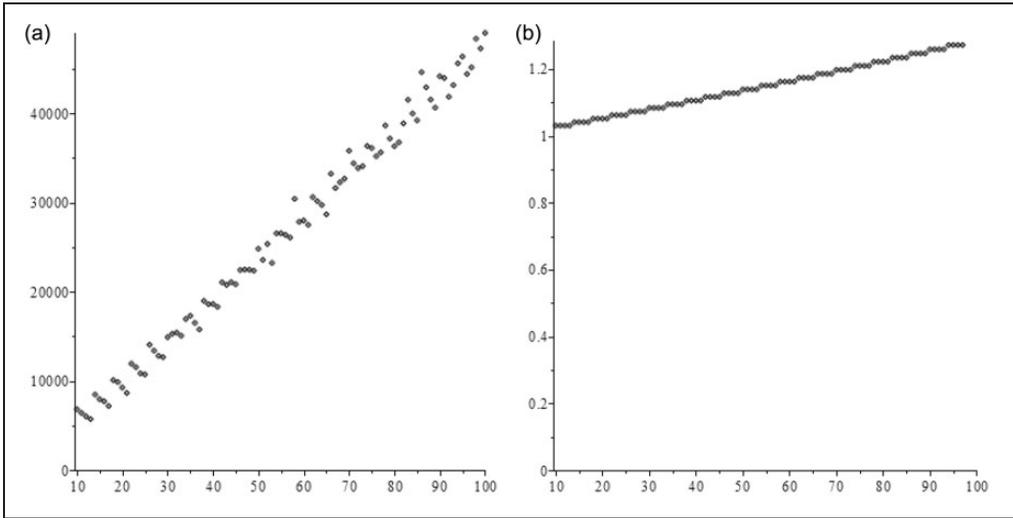


Figure 5. (a) Difference in demand between superstar and star as a function of choice set size for Model 3: $S_i = \sum_{j \neq i} (u(x_i) - u(x_j))$; one in four alternatives is used as reference point. (b) Ratio in demand between superstar and star as a function of choice set size for Model 3: $S_i = \sum_{j \neq i} (u(x_i) - u(x_j))$; one in four alternatives is used as reference point.

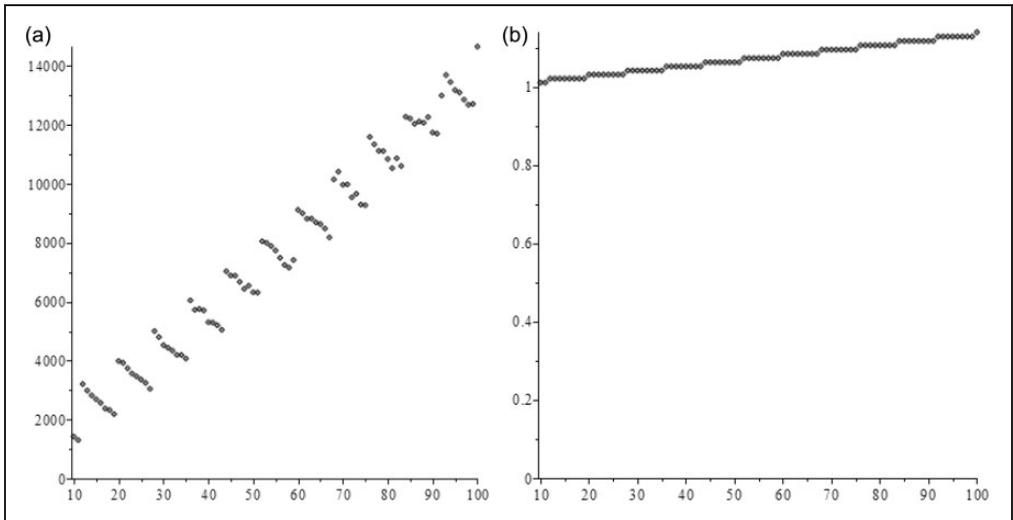


Figure 6. (a) Difference in demand between superstar and star as a function of choice set size for Model 3: $S_i = \sum_{j \neq i} (u(x_i) - u(x_j))$; one in eight alternatives is used as reference point. (b) Ratio in demand between superstar and star as a function of choice set size for Model 3: $S_i = \sum_{j \neq i} (u(x_i) - u(x_j))$; one in eight alternatives is used as reference point.

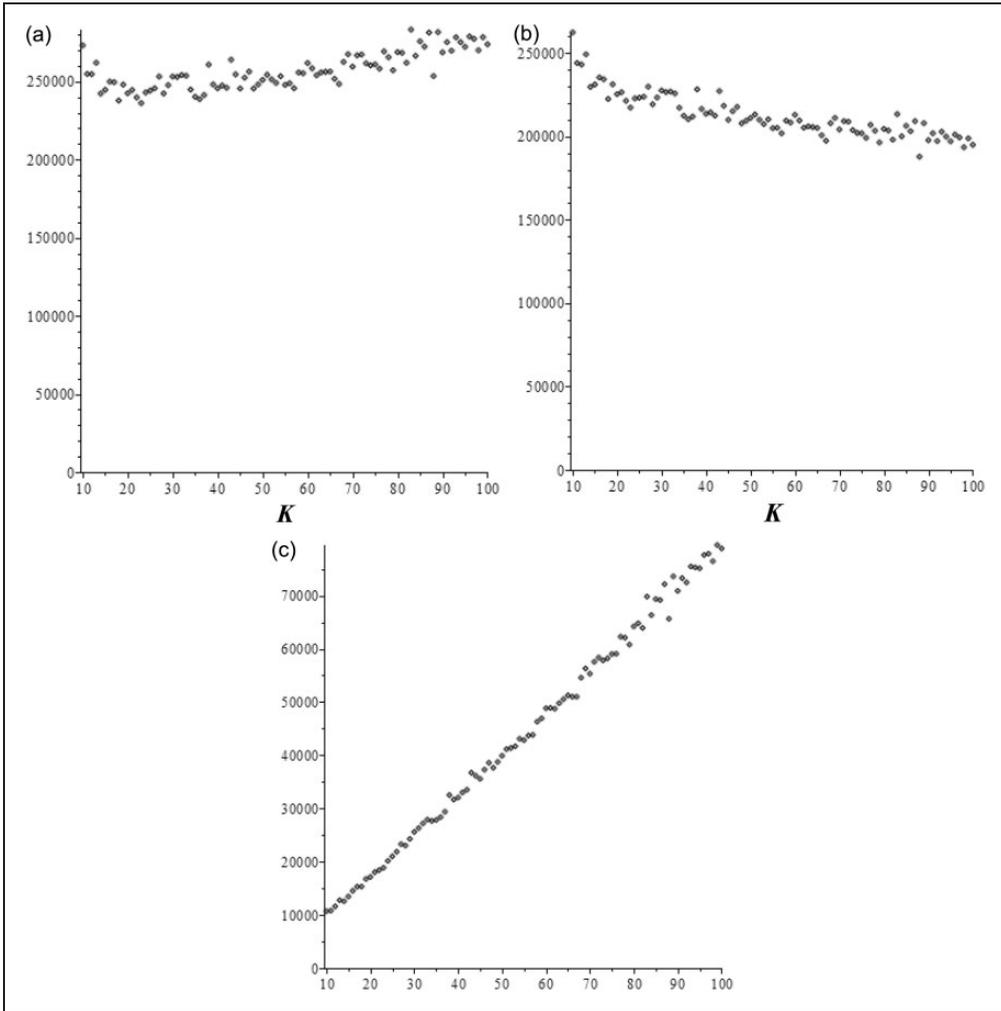


Figure 7. (a) Demand for the superstar as a function of choice set size for hybrid reference dependent model $S_i = 0.33 \dots \sum_{j \neq i} (x_i - x_j) + 0.66 \dots \cdot x_i$. (b) Demand for the star as a function of choice set size for hybrid reference dependent model $S_j = 0.33 \dots \sum_{j \neq i} (x_i - x_j) + 0.66 \dots \cdot x_i$. (c) Difference in demand between superstar and star as a function of choice set size for hybrid reference dependent model $S_i = 0.33 \dots \sum_{j \neq i} (x_i - x_j) + 0.66 \dots \cdot x_i$.

points, the reference dependent model – just like the linear and convex models – exhibits a decreasing difference in demand between the two stars when the destination choice set grows; note that as was the case for the other two candidate models, the demand ratio then still remains constant.

To conclude this numerical part of the article, it may be noted that a hybrid model can be constructed which assumes that anticipated destination satisfaction is to some extent driven by reference dependent preferences and to some extent by absolute quality levels: $S_{in} = \rho \cdot \sum_{j \neq i} (x_{in} - x_{jn}) + (1 - \rho) \cdot x_{in}$, with $\rho \in [0, 1]$ indicating the extent to which satisfaction is driven by relative comparisons with competing alternatives (rather than by their absolute quality levels). Additional simulations, presented in Figure 7(a) to (c), show

that even when satisfaction is only to a small extent (i.e. for one-third) determined by relative comparisons between destinations, convex demand for quality arises – especially when the choice set size increases. More specifically, the figure shows that when destination choice sets are relatively small, the large weight on absolute (rather than relative) quality makes that both the superstar and the star destinations loose demand when new destinations are introduced to the set. As a result, the difference between the two destinations in terms of demand remains relatively small.

Note that, for reasons of succinctness, the ratio in demand between superstar and star destinations, which can be shown to equal $\exp(\rho \cdot 0.01 \cdot K) = \exp(\frac{0.01}{3} \cdot K)$ is not plotted. However, as destination choice set size grows, the trend is reversed in the sense that the superstar destination now starts to *gain* demand from the introduction of new destination and the (second-best) star destination loses demand simultaneously. The result is that for these larger choice sets, the difference in demand between the two highest quality destinations to an increasingly large extent starts to exceed the difference in quality, implying an increasingly convex demand for quality. In sum, as one would expect, the hybrid model which combines candidate model 3 (the reference dependent model) and the base model, generates superstar effects but the extent to which is less pronounced than is the case for the fully reference dependent model.

Conclusion and discussion

This article highlights the importance of superstar effects for urban planning, and it presents different destination choice models which each provide an explanation for the presence of convex demand for quality, which is an often-cited precondition for the existence of superstar destinations. The proposed models of decision-making do not assume that convex demand – and as a result: the existence of superstar destinations – is triggered by fixed consumption costs (which would likely be an incomplete representation of the behavioural premises underlying demand-convexity). Instead, the proposed models generate a convex transformation from destination quality to demand by assuming, respectively, (i) a linear utility function incorporating a very high level of sensitivity or changes in quality; (ii) a convex utility function; (iii) a reference dependent decision rules which postulates that decision-makers anticipate that the satisfaction associated with a destination depends on quality *comparisons* between that destination and each of the competing destinations in the choice set (rather than depending on absolute quality levels).

Using an analytical example and numerical simulations, the article shows that all three candidate destination choice models, each in their own way, have the potential to generate superstar effects. The linear model based on a high sensitivity for quality (reflected by ‘a large beta’) as well as the model based on a convex utility function, have the potential to amplify small differences in quality between star and superstar destinations into large differences in demand, in favour of the superstar. The size of the difference in demand however, was found to decrease with the size of the destination choice set; this is at odds with the notion that in real life, superstars are generally observed in situations where there are many alternatives to choose from as well as with evidence (Elberse, 2008) that increasing choice sets have led to a larger concentration of demand. A third candidate model generates superstar effects by means of a reference dependent decision rule. This model, in contrast with the other two candidate destination choice models, predicts that superstar effects become more pronounced (in terms of differences as well as ratios of demand) as destination choice sets grow larger; in this regard, the reference dependent model appears to be in line with real life observations. Further analyses also show even when only a relatively small subset of

destinations is included in the reference dependent evaluation process, superstar effects emerge.

Clearly, the analyses presented in this article are co-determined by the specific settings of the numerical experiment. Nonetheless, a series of sensitivity analyses – some of which are not reported here to avoid repetition – show that results (especially generic trends) appear to be robust with respect to variation in (i) parameters such as β, γ, ρ ; (ii) the distribution of destination quality levels (i.e. normal vs. uniform distribution; pre-set quality levels for star and superstar destinations); the specific form of the utility function embedded in the reference dependent model (e.g. results also hold when the utility function is concave as opposed to linear, and when performing worse is assigned more weight than performing better); etc.

Nonetheless, an important direction for future research relates to the empirical testing of the three candidate destination choice models. In terms of external validity, revealed preference data would of course offer the preferred testing ground. However, it may turn out to be difficult to adequately measure quality in a way that does not trigger confounding with demand. Take for example the situation where demand for museums is explored; a museum's quality might be measured by means of a proxy based on the total estimated monetary value of its collection. However, this value is itself a measure of demand as well. Such confounding makes it difficult to empirically identify superstar effects and their potential behavioural determinants. For such reasons, stated preference data might be needed to achieve the high level of experimental control over quality levels that is necessary to compare the empirical performance of the three candidate models (and possibly combinations thereof).

The finding that the proposed models predicts convex demand for quality without relying on minimization of (fixed) consumption costs, does not imply that the proposed models provide the most important (let alone, the only) explanations for the existence of convex demand for quality, or that consumption costs do not play a role as well. More generally speaking, subsequent research efforts should also be directed to other behavioural mechanisms that potentially generate superstar effects. Where this article focussed on decision rules and the functional form of destination choice models, there are at least two other avenues to be explored in this regard. Firstly, one could focus on the error terms embedded in the choice model. Whereas this article assumed i.i.d. errors (resulting in convenient Logit formulations for choice probabilities), it seems intuitive that an appropriately specified Nested Logit model could offer a partial explanation for superstar effects: if all destinations except for the superstar are placed into one nest, this should result in higher levels of competition (substitution) among alternative destinations within the nest, than between each of these destinations and the superstar. Secondly, one may explore the role of social networks, and particularly the potential of the so-called Matthew effect; see e.g. Wagner and Leydesdorff (2005) for a discussion in the context of scientific collaborations. This effect postulates that when part of people's preferences are based on the choices of others in their social network – see e.g. Dugundji and Walker (2005) for evidence of this phenomenon in a travel mode choice context – small differences in quality may over time, through snowballing, result in large differences in demand.

It is likely that a combination of different factors, including but not limited to (combinations of) the models proposed in this article, as well as minimization of consumption costs and possibly error term and social network related effects, jointly determines the existence of convex demand for destination quality and the associated existence of superstar destinations. Determining the importance of each factor and of their mutual interactions is ultimately an empirical, not a theoretical challenge that should

be addressed in future research; the LC framework, of which outlines were presented in An analytical framework to study potential superstar effects on empirical data section, provides a useful methodological starting point for such empirical research endeavours.

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Notes

1. If $1/J$ equals the fraction of destinations selected as reference points, then in the context of the particular simulation settings the ratio of demand between superstar and star destinations equals $\exp(K/J \cdot 0.01)$, which increases with destination choice set size and with the fraction of destinations selected as reference points, and is not affected by simulation noise.
2. In the simulation, for example the choice set size of 83 destinations was divided by 8 and then rounded to the nearest integer to arrive at the number of destinations used as reference point – being 10 in this particular case.

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