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RESEARCH ARTICLE

On the determinants of tourism performance

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ABSTRACT

The purpose of this paper is to propose an innovative direction in order to analyze the determinants of tourism performance. The literature on this topic reveals diverging results about the impacts of the determinants of tourism performance. This paper advocates for the identification of the multiple and complex effects of the determinants in order to overcome the characterization of single net effects derived from an average behavior. A two-stage efficiency analysis is implemented, mixing Data Envelopment Analysis and fuzzy-set Qualitative Comparative Analysis. An illustration about the tourism efficiency in French regions is proposed and emphasizes the multiple impacts of the determinants.

Introduction

Performance modeling in tourism research received a great attention from scholars this last decade (Assaf & Tsionas, 2019). Several techniques are available in the literature in order to model tourism performance. Among others, Data Envelopment Analysis (DEA) and its derivatives is very popular. As identified by Assaf and Tsionas (2019, p.274), a key point in tourism performance analysis is the question about the determinants of efficiency. In a first stage, efficiency scores are calculated by using non-parametric approaches based on linear programming in the DEA framework. In a second stage, the efficiency scores are regressed by using determinants which are termed contextual or environmental variables in the literature. The goal is to explain their possible impacts on the efficiency level of the units analyzed and these two-stage approaches have been used extensively by tourism researchers (Assaf & Josiassen, 2016).

Different methods are available in the literature in order to explain the performance scores in the second stage analysis. Tobit regression was mainly used, but the technique changed with the important contribution by Simar and Wilson (2007). They provided a robust econometric technique based on bootstrapping. However, a debate about the method appeared with the work of McDonald (2009) who recommended regressions estimated by ordinary least squares for second stage analysis of efficiency. Simar and Wilson (2011) answered and proposed a demonstration of the robustness of their method. They underlined that their contribution in 2007 is the more appropriate but under very specific conditions. Finally, they argued in conclusion: "we do not recommend the use of second-stage regressions involving DEA efficiency scores" (Simar & Wilson, 2011, p.216). However, the analysis of the determinants of performance is still of paramount importance in tourism research and Assaf and Josiassen (2016, p.624) recommend to pay more attention on this topic. Given both the necessity and the uncertainty about the choice of the method for second stage analysis in the literature, this paper proposes an alternative way and advocates to use fsQCA (fuzzy-set Qualitative Comparative Analysis) for second stage analysis of tourism performance.

From a theoretical point of view, the reductionist approach, simplifying the analysis to the principal components of the

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phenomenon studied, has some limits in order to model the tourism sector (Baggio, 2008). Tourism is a complex phenomenon (Goeldner & Ritchie, 2012) that can be viewed as a complex system (Farrell & Twining-Ward, 2004). The relationships between the components of the tourism sector can be nonlinear (Urry, 2005). This is particular relevant in the analysis of tourism destinations in which multiple stakeholders are present (Baggio, Scott, & Cooper, 2010a, 2010b). Some studies have attempted to address the complexity of the tourism destinations by applying qualitative or quantitative methods (Baggio et al., 2010a). However, in our knowledge, none have tried to use qualitative comparative analysis (QCA) whereas this last offers the possibility of a middle path between qualitative and quantitative methods (Ragin, 2008). The fuzzy version of QCA, termed fsQCA, is a technique permitting to capture the complexity and was introduced by the sociologist Ragin (2008). It is based on the theory of complexity (Gigerenzer, 1991; Urry, 2005) and provides a real value to apprehend the complexity of the tourism sector. Contrary to regression analysis that identifies net effects, the advantage of this method is the characterization of multiple effects of the exogenous variables on the dependent variable. Accounting for complexity in the explanation of tourism performance seems particularly relevant since the tourism phenomenon is "complex" (Goeldner & Ritchie, 2012). Then this paper investigates the use of fsQCA in order to explain the DEA efficiency scores in tourism research.

In order to illustrate the use of fsQCA in efficiency second stage analysis, the case of tourism destinations is considered. Modeling tourism destination efficiency received a lot of attention in the literature (Tsionas & Assaf, 2014). The interest of this two-stage

Table 1
Impacts of the determinants of tourism efficiency.

Authors	Second stage	Units	Impacts	
			Positive	Negative
Barros and Dieke (2008)	Truncated regression	Angolan hotels	Ownership Market share International strategy	
Shang et al. (2010)	Tobit regression	Taiwanese hotels	Location Age Ecommerce Ownership	
Assaf and Agbola (2011)	Truncated regression	Australian hotels	Age Location Star rating (quality) Size	
Barros et al. (2011)	Truncated regression	French regions	Monuments Beach Theme park Ski Natural park Museums	
Huang, Mesak, Hsu, and Qu (2012)	Tobit regression	Chinese provinces	International attractiveness Education Earnings	Trade openness Time
Benito et al. (2014)	Truncated regression	Spanish regions	Beach Museums Ski Natural areas Cultural heritage MICE Golf Gastronomy Shopping	
Oukil et al. (2016)	Truncated regression	Oman hotels	Star rating (quality) Culture Activities	Nature (beach, etc.) Ownership Size
Cuccia et al. (2016)	Truncated regression	Italian destinations	Sea Culture Environment	Theft Time trend WHL Unesco
Solana-Ibáñez et al. (2016)	Truncated regression	Spanish regions	Beach Museums Natural areas Cultural heritage MICE Gastronomy Shopping	Ski Golf
Sellers-Rubio and Casado-Díaz (2018)	Truncated regression	Spanish regions	International tourists Length of stay Sun and sand	Quality
Chaabouni (2019)	Truncated regression	Chinese provinces	Trade openness Temperature Urbanization	Education Number of hotels Geographical localization

approach is illustrated with the French regions (Barros, Botti, Peypoch, Robinot, & Solonandrasana, 2011; Botti, Peypoch, Robinot, & Solonadrasana, 2009) and by using the tourism attraction theory (Leiper, 1990; Lew, 1987) in order to select the determinants. For a comparative purpose, the Simar and Wilson (2007) method is also implemented.

The paper unfolds as follows. The determinants of tourism efficiency: current gap section presents a literature review in order to identify the research gap. Methodologies section briefly introduces the background of DEA and fsQCA. Application to the French regions section proposes an empirical illustration. Conclusion and future research section concludes and underlines a methodological question for future research.

The determinants of tourism efficiency: current gap

In tourism performance modeling, the two-stage approach with the DEA method is widely used (Assaf & Josiassen, 2016). On the one hand, scholars use the DEA method and its derivatives to measure the tourism performance at a micro or macro level (hotels, restaurants, airports, destinations, etc.) and to obtain a benchmarking analysis. On the other hand, they employ methodologies based on regressions such as Tobit or bootstrapping techniques with a truncated distribution in order to identify the determinants of tourism performance.

The purpose of this section is not to provide another literature review on the determinants of tourism efficiency in the extensive existing literature (Assaf & Josiassen, 2012; Assaf & Josiassen, 2016; Sellers-Rubio & Casado-Díaz, 2018). In order to identify the current gap this paper intends to reduce, we focus on the net effects identified in the empirical literature devoted to the determinants of tourism efficiency. More precisely, we point out some examples of opposite or contradictory findings in empirical contributions in order to highlight the determinants in which there is no consensus in the literature.

The literature devoted to hotel efficiency shows several examples of diverging results. For instance, destination quality can have different impacts on efficiency (Sellers-Rubio & Casado-Díaz, 2018) and the link between hotel size and performance shows no real consensus (Oukil, Channouf, and Al-Zaidi (2016). At a destination level, the variable beach affects positively the tourism regions in France (Barros et al., 2011) whereas it plays a negative role in the tourism performance in Oman (Oukil et al., 2016). For the variable related to monuments, Barros et al. (2011) show a positive impact on French tourism performance while Cuccia, Guccio, and Rizzo (2016), by using the World Heritage List, find a negative impact for the tourism efficiency in Italy. In two applications to the Spanish regions that differ according to the time-periods studied and in which all the variables used are the same, Benito, Solana, and López (2014) and Solana-Ibáñez, Caravaca-Garratón, and Para-González (2016) find different findings concerning the impact of ski and golf attractions. Another example of diverging results includes the variable hotel ownership with a positive impact in the study by Barros and Dieke (2008) and Shang, Wang, and Hung (2010) while Oukil et al. (2016) identify a negative impact. The same applies for the size effect in the hotel sector which can be a positive (Assaf & Agbola, 2011) or a negative (Oukil et al., 2016) impact. Table 1 summarizes these different impacts in some empirical contributions of the literature.

This survey permits to identify a gap in the literature. Indeed, the determinants of tourism performance can have different effects according to the case and the scale studied, showing an interesting feature of the complexity of the tourism sector.

This paper contributes to reduce this gap and innovates by considering the complexity in the determinants of tourism performance. In words, the use of fsQCA in second stage DEA models permits to consider multiple effects instead of net effects.

Methodologies

This section presents and develops a two-stage procedure based on a combination between two existing methodologies: DEA and fsQCA. The objective is to model the tourism performance by using DEA and to identify its determinants in a second stage with the fsQCA approach.

DEA method

The DEA method proposes an analysis of performance through the notion of efficiency. It is a non-parametric approach based on linear programming. DEA was introduced by the works of Charnes, Cooper, and Rhodes (1978) and Banker, Charnes, and Cooper (1984), which differ regarding the assumption on returns to scale of the production technology, respectively constant and variable. DEA is a well-known and useful method for managerial and strategic purposes. Its two main advantages are related to the possibility to deal with multi-input/output production technologies and to not assume a functional form for this latter.

DEA measures the relative efficiency of a given sample of decision making units that transform inputs into outputs. The production technology of the decision making units transforms the inputs $x=(x_1,\cdots,x_N)\in R_+^N$ into the outputs $y=(y_1,\cdots,y_M)\in R_+^M$. In other words, the production technology T can be rewritten as $T=\{(x,y)\in R_+^{N+M} : \text{x can produce y}\}$ and is defined by:

$$T=\left\{(x,y):x\geq\sum_{i=1}^{k}\theta_i x^i, y\leq\sum_{i=1}^{k}\theta_i y^i,\theta_i\geq0, i=1,\cdots,k.\right\}$$

The linear program for computing the efficiency score of the DEA model (Charnes et al., 1978) of each decision making unit is given by:

$$Max\ \delta$$

$$s.t.x \geq \sum_{i=1}^{k} \theta_i x^i$$

$$\delta y \leq \sum_{i=1}^{k} \theta_i y^i$$

$$\theta_i \geq 0, i = 1, \cdots, k.$$

This program is run k times, k corresponding to the number of units analyzed in the sample. This model is output oriented, a common practice in tourism destination management because the objective is to maximize the results (Dong, Peypoch, & Zhang, 2020). The DEA model by Banker et al. (1984) can be obtained by adding the constraint $\sum_{i=1}^{k} \theta_i = 1$ in the previous linear program in order to account for variable returns to scale. Assaf and Josiassen (2016) and Assaf and Tsionas (2019) propose recent surveys of empirical contributions using DEA in tourism research.

fsQCA approach

fsQCA is a set-theoretic method that comes from political and social sciences. It is a set of approaches based on connections between several relationships developed by Ragin (1987, 2008). Ragin exposes this approach in detail by showing that set-theoretic connections are asymmetrical whereas correlational connections are symmetric. This method is based on the complexity theory and can be applied to small, medium and large samples (Ragin, 2008). Recently, Woodside (2014, 2015) explained the interest and advantages for scholars to use fsQCA in management sciences. According to Woodside (2014), the complexity theory involves the following six tenets: i) a single condition can be necessary but it is rarely sufficient to explain a result. ii) A small number of configurations (or combinations of conditions) are sufficient; it is the recipe principle. This latter is composed of two or more conditions in order to explain the result with a high consistency score. iii) A simple antecedent condition can contribute positively or negatively to the result, depending of its association with other conditions. iv) The equifinality principle: several paths or configurations lead to performance. v) The causal asymmetry principle: paths leading to a high performance are not the opposite mirror to the paths leading to a low performance. vi) A given configuration is not relevant for all cases.

Woodside (2015, p.253) provides also an interesting explanation about the comparison between fsQCA and regression analysis. The endogenous variable in the regression is the outcome condition (or result) in fsQCA while the exogenous variables are the antecedent conditions. Regression-based approaches analyze the net effects of the variables and focus on the explanatory power of the model (measured by R^2) while fsQCA identifies configurations, i.e. combinations of conditions, which lead to the result with the most consistent accuracy possible (measured by the consistency index).

The determination of the configurations in order to model and explain the complexity of the phenomenon studied requires different stages. The first stage is the calibration of the variables. It is a crucial step and, according to Ragin (2008), it must be based on the most complete knowledge from the researcher. Three main points or thresholds are considered (full nonmembership, crossover and full membership) with calibrated values equal respectively to a fuzzy score between 0 and 1 (respectively 0.05, 0.5 and 0.95). The second step is the necessity analysis. By using Boolean algebra, fsQCA estimates indexes of consistency and coverage to analyze the necessity. According to Ragin (2008, p.44-45), the notions of consistency and coverage can be explained as follows. Consistency measures a kind of degree of significance insofar as it underlines if the researcher has to pay attention or not to a configuration regarding the theory. Coverage indicates a kind of degree of importance of a configuration.

For the necessity analysis, the consistency index is based on the following formula (Ragin, 2008):

$$\text{Consistency}(X_i \geq Y_i) = \frac{\sum[min(X_i, Y_i)]}{\sum(Y_i)}$$

The calculation of the coverage index is defined by:

$$\text{Coverage}(X_i \geq Y_i) = \frac{\sum[min(X_i, Y_i)]}{\sum(X_i)}$$

where X_i is the calibrated antecedent condition and Y_i is the calibrated outcome condition for the unit i.

A condition is necessary if its consistency index is greater than or equal to 0.9 (Ragin, 2006, 2008). The next step is the construction of the truth table. This configuration table provides all the logical configurations between causality conditions in order to obtain the result with a level of empirical evidence associated with each configuration. It is composed of 2^k lines where k represents the number of conditions (variables). The number of lines retained depends of the consistency cutoff and the frequency threshold selected. Finally, the identification of sufficient configurations is done by using Boolean minimization and the Quine-McCluskey algorithm. The corresponding consistency and coverage indexes for sufficiency analysis are defined by Ragin (2008):

$$\text{Consistency}(X_i \leq Y_i) = \frac{\sum[min(X_i, Y_i)]}{\sum(X_i)}$$

$$\text{Coverage}(X_i \leq Y_i) = \frac{\sum[min(X_i, Y_i)]}{\sum(Y_i)}$$

where X_i is the calibrated antecedent condition and Y_i is the calibrated outcome condition for the unit i.

Application to the French regions

Tourism in France is characterized by a paradox which shows the relative inefficiency of the French destination at the international level when tourist arrivals and tourism receipts are compared (Barros et al., 2011). This weakness of the French tourism sector motivated scholars to analyze and benchmark the best practices at the regional level on the French territory. Hence, modeling the tourism performance of the French regions received some attention in the literature (Barros et al., 2011; Botti et al., 2009; Corne, 2015). In this line, this paper revisits the determinants of the tourism performance of French regions by using fsQCA in the second stage of the DEA framework.

The 13 French administrative regions are considered for this study. The territorial reform changed the number of French regions from 22 to 13 since 2016. This is of particular importance for efficiency analysis as the literature clearly shows that, in order to be discriminatory in terms of efficiency, some rules are required between the number of units in the sample and the number of inputs and outputs (Sarkis, 2007). In general, but without real consensus, the number of units is expected to be greater or equal to three times the sum of inputs and outputs (Cooper, Seiford, & Tone, 2006) or larger than two times the product of the number of inputs and outputs (Dyson et al., 2001). Then, a production technology with two inputs and two outputs is considered. The variables are selected by following the literature and according to the data availability. The two inputs are accommodation capacity in the hospitality sector (number of rooms) and number of employees in the tourism sector (Sellers-Rubio & Casado-Díaz, 2018). These two inputs characterize capital and labor and are commonly used in tourism performance studies (Assaf & Josiassen, 2016). The two outputs are the number of tourist arrivals and the tourist tax. These two outputs permit to capture the attractiveness and the economic repercussions of the tourism flows. The number of tourist arrivals is commonly used in frontier research in tourism (Assaf & Josiassen, 2016). The tourist tax is more innovative in terms of output and it is a good proxy at the regional level when tourism revenue is unavailable (like in the French official statistics). Finally, all the inputs and outputs are expressed in value, without proportion data in order to avoid bias in the DEA estimation (Olesen, Petersen, & Podinovski, 2017).

Data for the inputs and outputs are sourced from the "Mémento du tourisme, 2018" for the year 2017 and are available at: https://www.entreprises.gouv.fr/etudes-et-statistiques/

Table 2 presents the descriptive statistics of the inputs and outputs used.

Regarding the variables for the second stage analysis, a focus is made on tourism attraction theory. Since the works of Lew (1987) and Gunn (1988), it has been commonplace to consider tourism attraction as a key element of the tourism supply side. Leiper (1990) extended the characterization of the tourism attraction and several classifications appeared in the literature (Beckendorff, 2006; Botti, Peypoch, & Solonandrasana, 2008; Gunn & Var, 2002). Swarbrooke (2002) showed the importance of the tourism attractions in the development of the destination and they have also a core place in the conceptual framework of destination competitiveness of Ritchie and Crouch (2003) for the destination management organizations. In the empirical literature, the study of the impacts of tourism attractions on regional performance by using two-stage models is now well established (Barros et al., 2011; Benito et al., 2014). The case of the determinants of the French regional tourism performance is implemented by following the literature devoted to the impacts of tourism attractions on regional performance (Barros et al., 2011; Benito et al., 2014; Huang et al., 2012). In order to analyze the determinants of the French tourism performance, we follow these contributions and four variables are then considered: number of monuments, number of museums (labelled 'musées de France'), presence of beaches in the region, presence of ski resorts in the region. The number of museums is provided by the French Ministry of Culture (2018) and all the other data are sourced from the Mémento du Tourisme (2018) for the year 2017.

From a theoretical point of view, the expected impact of a tourism attraction is positive. This is confirmed for these four determinants by a large part of the empirical literature and more precisely with a previous study by Barros et al. (2011) for the French tourism regions. However, the complexity of the tourism sector can reveal some contradictory findings (Table 1).

With the territorial reform, the French regions are more homogeneous in terms of size. Then the DEA model with constant returns to

Table 2
Descriptive statistics.

	Max	Min	Mean	Standard dev.
Inputs and outputs				
Employees	420,498	8442	100,688	105,194
Capacity	156,405	12,517	49,328	39,280
Arrivals	33,812	1477	9068	8184
Tourist tax (million €)	100.3	1.05	17.8	27.3
Determinants				
Monuments	1871	140	1122	451
Museums	143	10	95	42
Beach	1	0	0.62	0.51
Ski	1	0	0.38	0.51

scale (Charnes et al., 1978) is used and this choice is confirmed by a test on returns to scale implemented by following the procedure proposed by Bogetoft and Otto (2011) and by using the package 'benchmarking' in the R software (R Core Team, 2019).

The findings of the output-oriented DEA model with constant returns to scale are presented in Table 3.

In 2017, the average efficiency level of French regions is 91.82%. Four regions are technically efficient. In terms of relative efficiency, these findings are in line with previous research, especially concerning the region Ile-de-France that is technically efficient and constitutes the main benchmark (Barros et al., 2011; Botti et al., 2009). Provence-Alpes-Côte d'Azur and Corse are two other regions technically efficient which are very reputed for their beaches. The efficiency scores of other cases like the region Bourgogne-Franche-Comté can be explained by the merger of regions with the territorial reform. The lowest region is Auvergne-Rhône-Alpes with a relative efficiency level of 76.66% characterized by a shortfall of 30.45% in the outputs production, confirming that this region is too big in size (Corne, 2018).

For the second stage with fsQCA, all the calculations are made by using the fs/QCA 2.5 software (Ragin & Davey, 2014). The calibration of the variables is the first step. Concerning the efficiency score and the explanatory variables monuments and museums, the thresholds are selected by using a cluster analysis (Cronqvist, 2004) and the researcher knowledge (Ragin, 2008). The calculations are done with the Tosmana software (Cronqvist, 2016). The variables beach and ski are dummy variables coded 1 for presence and 0 for absence. For the efficiency score, as the model is output-oriented, the calibration is made on the inverse of the score. Table 4 presents the calibration of the variables.

Table 5 shows the results of the necessity analysis. The tests are performed on the efficiency score variable after calibration (score-c) and its negation (~score-c). Clearly, none condition is necessary for the presence or absence of efficiency because all the consistency indexes are less than 0.9 (Ragin, 2008). In other words, the presence or absence of one of these four explanatory variables is not necessary to explain the performance of French regions.

The truth table translates the causal combinations and indicates the number of cases in each of them. Theoretically, 16 (2^4) combinations are possible but, in this study, only 10 combinations have at least one case. A frequency threshold (number of cases) is fixed and only the configurations with a minimum cutoff value for consistency are fuzzy subsets of the outcome. As recommended by Ragin (2008, p.136), for macro level data, a minimum cutoff value for consistency of 0.85 is selected. Regarding the frequency threshold, as the sample of this study is small; a value of 1 case is selected. Four combinations are then retained. It means that at least one case is present in each of these four causal combinations which have a consistency of at least 0.85. They are designated as fuzzy subsets of the calibrated performance variable. The sufficient configurations are finally obtained by using the Quine-McCluskey algorithm and the intermediate solution recommended by Ragin (2008) is presented in Table 6. Three complex configurations are sufficient to explain the French tourism performance with a high level of consistency.

Combination (1) ~monuments-c*beach-c*ski-c indicates that 98.5% of the empirical evidence is consistent with the fact that this configuration is sufficient to generate the performance of French regions. This solution covers 27% of the cases.

From a managerial point of view, the presence of beach and ski associated with the absence of monuments is a path leading to performance. This configuration suggests that the performance of the region can be explained by the presence in the territory of attractions linked to ski and beach activities. Such regions are very popular and attract a large number of tourists. Fig. 1 illustrates this configuration. The regions Corse and Provence-Alpes-Côte d'Azur are typical cases (Schneider & Rohlfing, 2013, p.595). This figure shows also that regions such as Bourgogne Franche-Comté and Ile-de-France reach a high level of relative efficiency without this configuration. By considering this path, these cases are deviant for coverage and thus they can be explained by another configuration.

The third combination (3) monuments-c*museums-c*~beach-c*~ski-c indicates that 93% of the empirical evidence is consistent with the fact that this configuration is sufficient for the French regions in order to be efficient. This solution covers 40% of the cases.

Table 3
Tourism performance of French regions in 2017.

Region	Efficiency level	Output shortfall (in %)
Auvergne-Rhône-Alpes	0.7666	30.45
Bourgogne-Franche-Comté	1	–
Bretagne	0.8484	17.87
Centre-Val de Loire	0.9711	02.98
Corse	1	–
Grand Est	0.9335	07.12
Hauts-de-France	0.9252	08.08
Ile-de-France	1	–
Normandie	0.8915	12.17
Nouvelle Aquitaine	0.8654	15.55
Occitanie	0.8859	12.88
Pays de la Loire	0.8484	17.87
Provence-Alpes-Côte d'Azur	1	–
Mean	0.9182	–
SD	0.0748	–

Note: i) In output orientation, the DEA score is greater or equal to 1. The efficiency level is derived from 1/score and indicates the percentage level of efficiency. ii) For inefficient units, shortfalls in output production are obtained by score - 1. For instance, the Occitanie region is inefficient with a relative efficiency level of 88.59% and it should improve simultaneously the two outputs by 12.88%.

Table 4
Calibration of variables.

	Thresholds		
	0.95	0.5	0.05
Efficiency score	0.98	0.9	0.82
Beach	1	0.5	0
Ski	1	0.5	0
Monuments	1438.25	1005.5	572.75
Museums	118.5	76	25

Table 5
Necessity analysis.

	Score-c		~ score-c	
	Consistency	Coverage	Consistency	Coverage
Monuments-c	0.6199	0.5995	0.7933	0.5399
~ monuments-c	0.5242	0.7828	0.4115	0.4325
Museums-c	0.772	0.6655	0.7412	0.4497
~ museums-c	0.3617	0.6651	0.4488	0.5807
Ski-c	0.3578	0.6423	0.3743	0.4729
~ ski-c	0.7064	0.616	0.7169	0.44
Beach-c	0.536	0.521	0.7914	0.5414
~ beach-c	0.5282	0.7825	0.2998	0.3126

Note: "-c" means calibrated variable; "~" is the negation of the variable.

Table 6
Sufficiency analysis.

Frequency cutoff: 1			
Consistency cutoff: 0.9307			
	Raw	Unique	
	Coverage	Coverage	Consistency
(1) ~monuments-c*beach-c*ski-c	0.2674	0.2005	0.9855
(2) ~monuments-c*~museums-c*~beach-c*~ski-c	0.1468	0.0537	1
(3) Monuments-c*museums-c*~beach-c*~ski-c	0.3996	0.2726	0.9307
Solution coverage: 0.6304			
Solution consistency: 0.9582			

It is interesting to note here that the absence of beach and ski associated with the presence of museums and monuments permits to explain the tourism performance. This configuration suggests a form of cultural tourism without the mass tourism effect that can be observed in French regions where beach and ski are present. This is typically the case for Bourgogne Franche-Comté and Ile-de-France regions.

These two configurations (1) and (3) show that different kind of attractions such as beach, ski and monuments can play different roles in order to explain the tourism performance depending on their association with other variables. Another interesting insight is that beach and ski resorts explain a high level of performance when they are associated in configuration (1). In other words, the presence of one of these attractions alone is not sufficient. This permits to understand the case of the region Auvergne Rhône-Alpes which has the biggest ski resorts of the French territory, but without coastline and that is the most inefficient unit.

The configuration (2) is more complex to interpret but it characterizes very few cases with a low coverage and then it can be omitted. Indeed, the coverage of an acceptable and informative solution is between 0.25 and 0.65 (Woodside, 2013, p.468) and this is not the case for this configuration.

The findings of this study also confirm the tenets of the complexity theory for the case of tourism destinations. A single tourism attraction is not sufficient to obtain a high efficiency level. A high efficiency level is explained by a complex combination with at least two or more tourism attractions and this is the case of the three configurations obtained in Table 6. A single tourism attraction can have both a positive and negative impact depending on its association with other kind of attractions. A high efficiency level can be reached by three different configurations. The configurations explaining a low efficiency level are not opposite to the configurations obtained for a high efficiency level; the fsQCA procedure has been implemented separately on the negation of the calibrated score (low level of performance) and all the complex configurations are different from the configurations obtained in Table 6, confirming the causal asymmetry principle. A given complex configuration explaining a high efficiency level is not relevant for all cases; indeed, the coverage index is less than 1 for each complex combination.

To ensure the robustness of our analysis, we do not limit the findings to fit validity and predictive validity is also performed

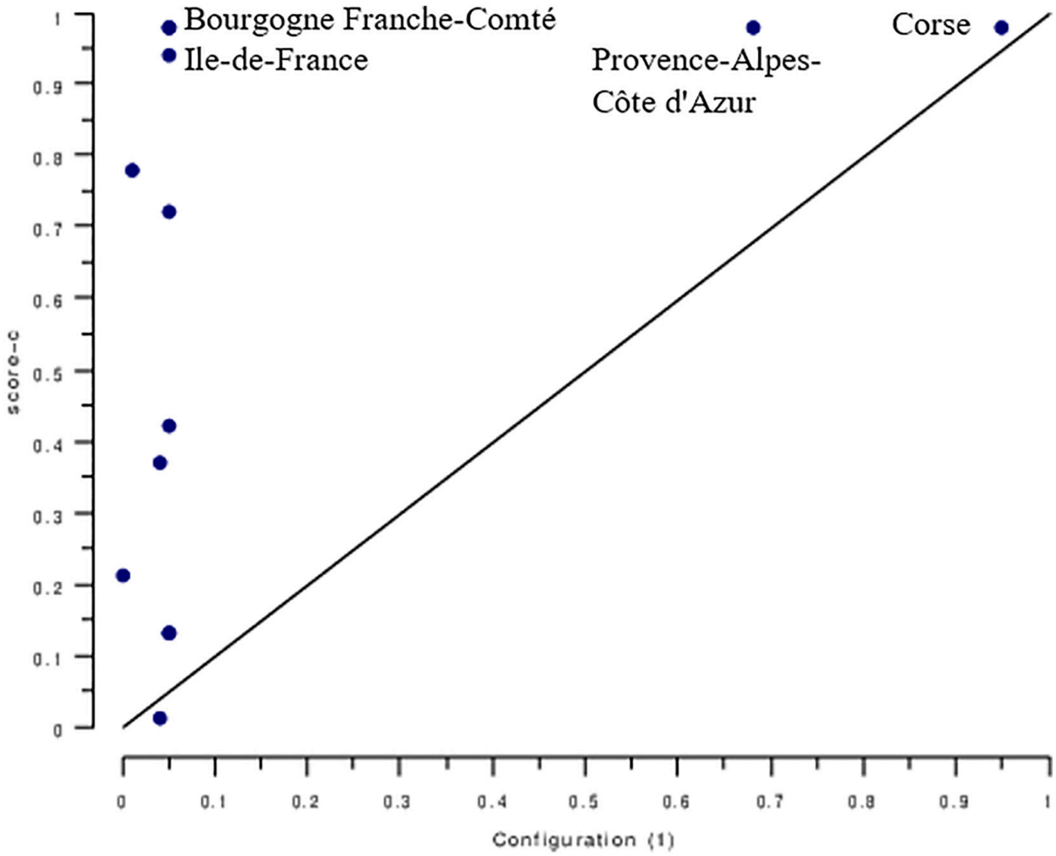

Fig. 1. X-Y Plot for sufficient configuration (1).

(Woodside, 2016). Predictive validity can be done when different time-periods are available or by splitting the sample into two subsamples, a modeling and a holdout subsample (Pappas, 2018, 2019). By using the same data sources, we consider the year 2016 in order to test the predictive validity of the configurations we obtained in Table 6 for 2017. First, DEA efficiency scores are estimated and the same four regions are again technically efficient. Second, the fsQCA procedure is done and the three configurations identified in Table 6 obtain a high consistency index. More precisely, configurations (1) and (3) obtain respectively 0.981 and 0.901 for the consistency index and 0.235 and 0.315 for the coverage index, suggesting that these models have a good predictive validity.

For a comparative purpose, Table 7 shows the findings of the bootstrapped truncated regression proposed by Simar and Wilson (2007). Calculations are implemented with the R software by using the rDEA package (Simm & Besstremyannaya, 2020). The number of replications is 2000 and, as the dependent variable is greater or equal to 1, a coefficient with a positive sign is associated with an improvement of inefficiency.

The only finding in line with the study by Barros et al. (2011) is about the variable museums which positively impacts tourism efficiency. For the variables monuments, ski and beach, the results are opposite. Although the sample (before and after the reform, respectively 22 and 13 units), the production technology and the years studied are not the same, this result is another example of contradictory empirical studies in the literature. Furthermore, the limitation of such approaches, based on net effects, is that managerial recommendations are restrictive. For instance, what are the propositions for decision-makers of regions with few museums? Clearly, accounting for complexity with the identification of multiple effects enlarges the explanation of the phenomenon and the possible recommendations. The French case, as an illustrative example, shows that regions cannot be summarized by an average

Table 7
Bootstrapped truncated regression results.

Constant	1.0818***
Monuments	0.0002**
Ski	0.1765***
Beach	0.036
Museums	−0.0017**

Note: ** and *** mean respectively statistically significant at 5% and 1%.

behavior. Indeed, the French regions have different kind of resources and attractions and they can achieve a high level of efficiency in different ways.

Conclusion and future research

This paper advocates to consider complex relationships in the analysis of the determinants of tourism efficiency. An illustration of the complexity of the tourism sector is provided by considering the French destinations at the regional level. In a first stage, the relative efficiency of French tourism regions is computed by using DEA. In a second stage, several determinants of the tourism performance are selected by considering the tourism attraction theory. These determinants are analyzed with fsQCA in order to highlight and to identify complex combinations. The findings of this paper are twofold. First, the findings confirm the complexity of the tourism destinations. A single tourism attraction is not sufficient and complex combinations of attractions should be considered in order to obtain a high level of performance. Hence, methods such as fsQCA should be used to deal with this complexity. Second, the results of this study overcome the limits of net effects analysis based on an average behavior. By using an asymmetric analysis and the tourism attraction theory, the recommendations for the decision-makers are based on complex combinations of conditions. A determinant can play a positive or negative role depending on its association with another determinant. This is the case for French destinations with tourism attractions such as beach, ski and museums. These complex solutions permit a better understanding of the tourism performance at the regional level.

The present paper has some limits. On the one hand, the territorial reform reduced the number of French regions and therefore the choice of the inputs and outputs is limited in order to implement efficiency comparisons based on DEA. The construction of the production technology is also subject to a constraint of data availability but alternative selections are possible before to analyze the impact of the determinants in the second stage. For instance, by including regional tourism receipts, a key economic indicator which is unavailable in France. On the other hand, some variables in the second stage can be measured by different ways. Beaches and ski resorts are examples that can be identified by binary variables (Benito et al., 2014) or by kilometers and numbers (Barros et al., 2011). This is of particular interest when they are treated in the QCA analysis as crisp or fuzzy variables (Ragin, 2008).

This paper provides some perspectives for future research. First, concerning the performance variable (the efficiency score) in the second stage by using fsQCA analysis, the calibration choice opens some methodological questions. Indeed, the efficiency score from the DEA method is between 0 and 1 when it is expressed in efficiency level with percentages. Then the question is how to calibrate it or not? Calibration is a crucial step in the use of fsQCA (Ragin, 2008) and it can be done by following researcher/expert opinions and by using statistical tools. In the context of destination management organizations, decision-makers could be useful in order to determine what is a membership or a nonmembership in terms of relative efficiency. This paper provides a direction for future research about the calibration of the efficiency score. Second, comparative analyses could be done with specific econometric techniques. Depending of the number of variables used in second stage, sufficient configurations could be compared with interaction terms in multiple regression analysis. Third, the analysis of the determinants with fsQCA could be done by distinguishing proximate and remote factors, depending on whether or not they are controllable by the decision-makers, with a two-step QCA (Schneider & Wagemann, 2006). Fourth, this paper has adopted a case study based on tourism attraction theory for the analysis of the determinants of tourism performance but other research questions can be considered to model the complexity of the tourism sector. At the macro level, the determinants identified in the conceptual models of tourism destination competitiveness can be mobilized to analyze destination performance. At the micro level, governance, environmental actions and quality are some examples of determinants to study the impact on the performance of tourism firms. Furthermore, this two-stage approach goes beyond tourism research and could be useful for other areas and economic sectors in which the performance analysis is of interest.

CRediT authorship contribution statement

The idea for using fsQCA in the DEA 2nd stage in a tourism context is from the PhD thesis of A. Corne (2016). A. Corne and N. Peypoch contribute equally to each part of the paper.

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