Tourism Management 96 (2023) 104722

Contents lists available at ScienceDirect

Tourism Management

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

Identifying a destination's optimal tourist market mix: Does a superior portfolio model exist?

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ARTICLE INFO

Keywords:
Portfolio theory
Destination management
Tourism portfolio models
Tourist markets
Diversification

ABSTRACT

Extant tourism research has used various portfolio model types to determine optimal tourist market mixes which simultaneously maximize total tourist expenditure and minimise the instability of international inbound tourism demand. We analyse the three portfolio models that have been applied in the tourism literature: two varieties of a levels model (that use the level of tourist arrivals, or bed nights to quantify tourist activity) and a growth rates model (that deploys the growth in the level of tourist activity). Applying these models using per capita expenditure in four distinctively different destination countries (Australia, Greece, Japan, and USA), we demonstrate that the Levels Model 1 is superior to the Levels Model 2 and the Growth Rates Model. It produces solutions that provide noticeably higher tourist expenditure with less instability of international tourism demand than the status quo. Theoretical contributions and practical implications for tourism policy makers and destination marketers are discussed.

1. Introduction

Tourism and travel have been growing significantly and exponentially from the 1950s until 2019 in terms of international tourism flows and international tourism spending, share of global GDP, and contribution to world employment. For instance, in 2019 international tourist spending constituted 27.4% of global services exports (WTTC & Oxford Economics, 2020). Notwithstanding the aforementioned increase in international tourist arrivals until 2019, the relative shares of international tourist arrivals and expenditures across the leading tourism destinations have changed over time. This is the result of the consolidation of emergent tourism destinations that have become more competitive than in the past (Botti et al., 2012;Mariani et al., 2014; UNWTO, 2018) Consequently, tourism policy makers and destination marketing managers have developed strategies to determine optimal tourist market mixes to maximize international tourism revenue and stability (Botti et al., 2012; Chen et al., 2011; Rakotondramaro & Botti, 2018.

The COVID-19 pandemic has had a damaging impact on the economic value created by travel and tourism activities since 2020, as the introduction of national and regional lockdowns and travel restrictions across the globe have generated an 87% (1 billion) fall in international tourist arrivals in the year. This has made 2020 the worst year in tourism history (UNWTO, 2021), and countries exposed to a high level of international tourism more subject to COVID-19 cases and deaths (Farzanegan et al., 2021). However, based on the estimates of a panel of experts, international tourism should be back to its pre-COVID level by 2023 (UNWTO, 2021). Accordingly, both tourism policy makers and destination managers – as well as tourism firms – are preparing to resume their activities; with the awareness that when they resume, international travel and tourism activities will have very high growth rates, potentially with more business opportunities than at present (Economist, 2021). The rebound of tourism is likely to renew attention by tourism policy makers and Destination Management Organizations (DMOs) on the most attractive and promising tourist markets; and strategies and tactics to devise optimal tourist market mixes to maximize

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https://doi.org/10.1016/j.tourman.2023.104722
Received 14 April 2022; Received in revised form 8 January 2023; Accepted 10 January 2023
Available online 16 January 2023

international tourism revenue and stability will need to be fine-tuned.

Traditionally, the objective of maximizing international tourism revenue and stability has to take into account that tourism destinations have particular infrastructure with limited accommodation, environment and transport capacity. For instance, recently the concept of "overtourism" has become popular (Koens et al., 2018), with limits on tourist capacity. As a consequence, both policy makers and destination marketers want to attract high spending tourist markets. As tourist expenditure differs between tourist markets, some tourist markets are more attractive than others. Destination policy makers may also wish to ensure that tourist income and employment do not fluctuate from year to year; and if most tourists belong to the same market, this exposes the destination to the risk of a drop in demand from that tourist market. This risk can be reduced by attracting a diverse tourist market mix.

Determining the optimal tourist market mix has been the objective of several studies over the last thirty years. More specifically, a research stream has leveraged financial portfolio theory (Markowitz, 1952) to model optimal tourist market mixes (e.g., Board et al., 1987; Board & Sutcliffe, 1991; Botti et al., 2012; Jang, 2004; Jang et al., 2004) often with the explicit intention of supporting DMO decision-making (e.g., Botti et al., 2012). Accordingly, determining the optimal tourist market mix has been modelled as a portfolio problem, where expenditure by the highest spending tourist market is traded off by tourism policy makers and destination managers against the higher risk of an undiversified portfolio. When setting policy some tourism researchers have applied what they term as 'portfolio analysis', where they compute various features of tourism (e.g. growth rates, market shares, growth of market shares, attractiveness, market relevance) from origin countries, e.g. Calantone and Mazanec (1991), Smeral and Witt (2002). This approach to setting policy for destination countries does not involve an optimizing model, and will not be considered. Destination marketing scholars segment tourists based on demographics, purpose of stay (travel vs. leisure), length of stay, mode of transport, type of accommodation, package versus independent travel, environmental impact, etc. However, past research using portfolio models has almost always segmented tourists by their nationality, in part because of a lack of good data for other segmentation variables; and in part because, in practice, destination marketers deploy nationality as the key variable of segmentation (Morrison, 2019). For a matter of consistency with previous research (e.g., Botti et al., 2012; Chen et al., 2011), and also to better clarify how different portfolio models compare to each other, we use nationality (also known as country of origin) as the segmentation variable in our four empirical examples. However, our analysis applies to any way of disaggregating tourists.

Three different portfolio models have been used by previous researchers – the Levels Model 1, the Levels Model 2 and the Growth Rates Model (GRM).[1] However, this literature has not addressed the following key research question: *Does a superior portfolio model exist for identifying a destination's optimal tourist market mix?* By addressing this research question, this study offers practical implications to tourism policy makers and destination managers dealing with international tourism, while making several theoretical contributions to the portfolio research stream within the context of tourism. First, to the best of our knowledge, this study is the first to investigate the differences between the three alternative types of portfolio model used so far in tourism portfolio research. Second, we recognize that there are upper and lower limits on the changes that tourism policy makers and destination marketers can implement in the tourist mix within the horizon period, and only half of the tourism portfolio literature has included upper and lower constraints on their policy variables (e.g., Board & Sutcliffe, 1991; Jang & Chen, 2008). We investigate the effects of this omission, and our results show it has a crucial effect. Third, this is the first study to illustrate and compare the results of applying the three existing tourism portfolio models to four distinctively different destination countries covering four continents and including Western and Eastern destinations, as well as destinations located in the Northern and Southern hemispheres. Fourth, from a methodological point of view, we investigate whether the application of a more sophisticated type of portfolio model (i.e., the Black-Litterman) changes the available trade-offs between total tourist expenditure and its variability, and the underlying mixtures of tourist nationalities.

We find that the Levels Model 2 and GRM models lead to infeasible policy recommendations, and that tourism policy makers should use the Levels Model 1 model when setting targets for the mix of tourist markets. We also argue that, while the Levels Model 1 and Levels Model 2 models have objectives that are in line with those of policy makers, The GRM is self-contradictory as it seeks to change individual growth rates, while treating the individual growth rates as parametric. Although the GRM is very widely applied to financial assets, we conclude that it should not be applied by tourism policy makers or destination marketers to determine the optimal tourist market mix.

2. Literature review

Portfolio theory was pioneered and introduced by Harry Markowitz (1952) for financial assets. The core idea of portfolio theory is not putting all your eggs in one basket, i.e. that for a given reward, risk can be reduced by diversification. This leads to a trade-off between maximizing a portfolio's expected reward (or return), and minimising its forecast risk as measured by its variance. More details about portfolio theory can be found in established literature (e.g., Bodie et al., 2021; Hillier et al., 2021).

Portfolio theory has also been applied to a lesser extent to other problems (Zopounidis et al., 2014) such as ecosystems (Alvarez et al., 2017), regional diversification by firms (Lande, 1994), the mix of coal and nuclear power generation (Sutherland, 1986), the farm crop mix (Collins & Barry, 1986), diversification of a county's exports (Love, 1978; 1979), diversification of the industries in a region (McKillop, 1990) and diversification of the benefits from admitting a country to the European Union (Goldberg & Levi, 2000).

In the travel and tourism policy and tourism management literature, the portfolio research stream using financial portfolio theory to model optimal tourist market mixes has used three different types of models. The Levels Model 1 minimises the variance of total tourist arrivals, bed-nights or expenditure for a given level of total arrivals or bed-nights or expenditure, and has been applied to Spain by Board et al. (1987), Board and Sutcliffe (1991) and Sinclair (1999). The Levels Model 2 minimises the risk of total tourist arrivals, bed-nights or expenditure, with no limit on the total level of tourist arrivals or bed-nights. This model has been applied to Croatia by Ivanovic et al. (2018), Canada by Jang (2004), France by Botti et al. (2012), Morocco by Ratsimbanierana et al. (2013), Taiwan by Jang and Chen (2008), Canada and the US by Jang et al. (2004), Australia by Johar et al. (2021), and without an empirical application by Arbel and Bargur (1980).

The GRM minimises variations in the growth rate of total arrivals, bed-nights or expenditure for a specified growth rate of total arrivals, bed-nights or expenditure, and has been applied to the US by Chen and Chen (2012), Japan by Chen et al. (2011), Ireland by Kennedy (1998), France by Rakotondramaro and Botti (2018 and French Polynesia by Botti et al., 2020). The GRM has also been applied by Buckley and Geyikdagi (1993) to minimise the variance of foreign exchange receipts from a mixture of tourism and exports for six Mediterranean countries,

[1] The Levels 1 and 2 models have been named in that way because they both use the level of tourist arrivals, or bed nights to quantify tourist activity. Although the Growth Rates model is mathematically equivalent to the Markowitz model, which uses returns, these models are not strictly the same; specifically, a major difference is that returns in the Growth Rates model are the percentage increase in the level of tourist activity, while in the Markowitz model they are the growth in the value of the shares plus any dividends and capital distributions. In the context of tourism 'returns' is inappropriate and is analogous to growth in the level of tourist activity.

including Greece. Overall, these three portfolio models (i.e., Levels Model 1, Levels Model 2, GRM) have been applied to tourism by segmenting tourists by nationality, although these models could use other segmentation variables. Subsections 3.1, 3.2 and 3.3 contain detailed explanations of these three models.

Although additional constraints could be added, a common feature of the three models is that they do not consider any restrictions on the implementation of tourism policy recommendations or destination marketing strategies, other than those on destination capacity and the size of the changes. For example, it may prove very costly to increase the bed-nights consumed by tourists of a particular nationality. Consistent with previous tourism portfolio literature, we assume that sufficient resources are available for marketing etc. to rebalance the tourist nationality mix to the desired proportions. If not, an additional financial resource constraint can be imposed on the portfolio model (see Board & Sutcliffe, 1991; Johar et al., 2021). We also assume, consistent with the previous tourism portfolio literature, that policy makers cannot, or choose not to, engage in initiatives to alter the input parameters of the portfolio model, e.g., reduce the variability of tourist bed-nights or increase expenditure per bed night for various nationalities.

Even if each nationality has the same expenditure per bed-night, this may not have the same multiplier effect on the national income of the destination country. For example, while one nationality may spend predominantly on imported goods and services with minimal effect on local incomes, another nationality may tend to spend on domestically produced goods and services, which leads to a larger increase in local incomes. However, there are no empirical estimates of the size of tourist income multipliers disaggregated by nationality. So, although the portfolio models can easily be adapted to include different income multipliers for each nationality, we implicitly assume that expenditure by each nationality has the same income multiplier. While incorporating nationality-specific income multipliers would change the nationality weights underlying the efficient frontiers, it would not affect our overall conclusion as to the superiority of the Level 1 model, as this does not depend on the specific nationality weights.

To provide a holistic illustration of the literature on tourism portfolio models, Table 1 includes all the studies that have been reviewed so far, clustered by model type (Levels Model 1, Levels Model 2, GRM). Our literature review of the individual tourism portfolio models continues in more depth in section 3 where each of the tourism portfolio models is reviewed in depth.

Three papers have used shortage functions, in conjunction with a levels version of the basic Markowitz portfolio model. None of these models include any upper or lower constraints on tourism for each nationality. They do not seek to find the efficient frontier, but rather the

Table 1
Articles that have Applied Portfolio Modelling in the Tourism Literature.

Authors	Country of Application	Period	Model Type
1. Board et al. (1987)	Spain	1966–85	Levels Model 1
2. Board and Sutcliffe (1991)	Spain	1966–86	
3. Sinclair (1999)	Spain	1966–86	
4. Arbel and Bargur (1980)	–	–	Levels Model 2
5. Botti et al. (2012)	France	1999–08	
6. Ivanovic et al. (2018)	Croatia	2002–16	
7. Jang (2004)	Canada	1998	
8. Jang and Chen (2008)	Taiwan	1996–05	
9. Jang et al. (2004)	Canada & US	1998	
10. Johar et al. (2021)	Australia	2008–17	
11. Ratsimbanierana et al. (2013)	Morocco	2006–10	
12. Botti et al. (2020)	French Polynesia	2014–17	Growth Rates Model
13. Chen and Chen (2012)	US	1991–06	
14. Chen et al. (2011)	Japan	1998–07	
15. Kennedy (1998)	Ireland	1969–95	
16. Rakotondramaro and Botti (2018)	France	2008–13	

improvement in the objective function from changing the bed nights or expenditure per bed-night for each nationality. These papers include the works by Botti et al. (2012) dealing with France, Ratsimbanierana et al. (2013) examining Morocco; and by Zhang et al. (2016), dealing with Nord-de-Calais, France. Another two studies have conducted a similar analysis, but using the growth rate of bed nights - Goncalves and Ratsimbanierana (2012) dealing with France; and Andriamasy and Rakotondramaro (2016) dealing with France. Since these papers answer a different research question, we intentionally do not include them in our literature review.

3. Tourism portfolio models

3.1. Levels model 1

The Levels Model 1 seeks to determine the optimal level of operation (the proportionate change in the level of arrivals, bed-nights or expenditure) for each national market to be targeted by tourist policy makers or destination marketers (e.g., Board et al., 1987; Board & Sutcliffe, 1991; Sinclair, 1999). The Levels Model 1 maximises the level of total tourist expenditure, while minimising the variance of total tourist expenditure. In the short to medium term, destinations have a limited supply of tourist accommodation and other infrastructure; so the Levels Model 1 includes an upper bound on total bed-nights, i.e. B in equation (1). Very large increases or decreases in the level of operation for a particular nationality induced by the tourism destination policies or strategies are unrealistic, and so the previous literature has imposed upper and lower constraints on the policy variables (the level of operation of each national market), e.g. AL and AU in equation (1). The lower constraints on the policy variables also obviate the need for the non-negativity constraints on the policy variables that are typically included in portfolio models.

The Levels Model 1 trades-off total tourist expenditure against its standard deviation; and is solved for a range of values of the total level of tourist expenditure. These variations in total tourist expenditure generate the frontier of efficient combinations of total expenditure and its standard deviation, with each point on this frontier corresponding to a different set of values of the policy variables. Tourism policy makers and destination marketers then need to select a particular point on this efficient frontier. If desired, the model can be modified by explicitly including the policy maker's/destination marketer's risk aversion, which then selects a particular point on the frontier. The Levels Model 1 allows the optimal solution to require reductions in the level of bed-nights for some nationalities to free up capacity for use by other nationalities/markets; although if capacity is expanding there need be no reduction in bed-nights for any nationality/market. The Levels Model 1 can be stated as:

$$\text{Min} \quad \Psi = (1/\mathrm{B})^2 \sum_{i=1}^{n} \sum_{j=1}^{n} x_i b_i x_j b_j \sigma_{ij} \quad \text{Minimise total expenditure risk} \tag{1}$$

$$\text{subject to} \quad \sum_{i=1}^{n} x_i y_i b_i = E \quad \text{A specified level of total expenditure}$$

$$\sum_{i=1}^{n} x_i b_i \le B \quad \text{Total bed} - \text{nights constraint}$$

$$AL_i \le x_i \le AU_i \forall I = 1 \ldots\ldots n \quad \text{Upper \& lower constraints on the policy variables}$$

where x_i is the targeted proportionate change in the level of bed-nights for nationality i next period, i.e. the level of operation for each tourist nationality (the policy variable).

y_i is the forecast level of expenditure per bed night for nationality i next period.
b_i is the forecast level of bed-nights for nationality i next period with unchanged policies.
E is the specified expected level of tourist expenditure, which is varied to generate the efficiency frontier.
σ_{ij} is the forecast covariance of the total expenditure by nationalities i and j, i.e. the covariances of y_ib_i and y_jb_j.
B is the forecast level of total bed-nights available next period.
n is the number of nationalities.
AL_i is the non-negative lower bound on the policy variable for nationality i.
AU_i is the non-negative upper bound on the policy variable for nationality i.

3.2. Levels model 2

The Levels Model 2 is also a levels model, but with some important differences from the Levels Model 1. The tourism policy variables are the proportions of total arrivals, bed-nights or expenditure accounted for by each tourist market. Therefore, the policy variables must sum to one. The Levels Model 2 is formulated with upper and lower constraints on the policy variables, i.e. *DL* and *DU* in equation (2), but has no constraint on total arrivals or bed-nights. This is because for real-world applications, including those we report below, including a constraint on both total bed-nights and upper and lower constraints on the policy variables makes the Levels Model 2 infeasible. Therefore, the Levels Model 2 is theoretically inferior to Levels Model 1 as it cannot have a constraint on total capacity, making it less realistic. In the Markowitz portfolio model, the return on a portfolio is the weighted sum of returns on the individual assets (Zopounidis et al., 2014). For Levels Model 2 the expected 'return' on a portfolio of nationalities is the weighted forecast level of arrivals, bed-nights or expenditure for each nationality (its 'return'). This is set equal to the average specified level of arrivals, bed-nights or expenditure across all nationalities, i.e., total forecast arrivals, bed-nights or expenditure multiplied by the number of different nationalities e.g. *E* in equation (2).

The Levels Model 2 specification below minimises the risk of total expenditure in terms of its standard deviation, with upper and lower constraints on the policy variables (i.e. the *z's* in equation (2)), but no upper constraints on total bed-nights or arrivals. This is the version of Levels Model 2 solved by Ivanovic et al. (2018). Jang et al. (2004) dropped the upper and lower constraints on the policy variables in their version of Levels Model 2, while Jang and Chen (2008) minimised arrivals risk with constraints on the policy variables, and Jang (2004) minimised bed-nights risk with no constraints. Johar et al. (2021) introduced a budget constraint, rather than a capacity constraint, but did not include restrictions (upper and lower constraints) on the size of changes from the current situation. Arbel & Bargur (1989) mention resource constraints, but did not include them, or upper and lower constraints on the policy variables.

$$\text{Min} \quad \Psi = \sum_{i=1}^{n}\sum_{j=1}^{n} z_i z_j \sigma_{ij} \text{ Minimise total expenditure risk} \tag{2}$$

$$\text{subject to} \quad n\sum_{i=1}^{n} z_i y_i b_i = E \text{ A specified level of total expenditure}$$

$$\sum_{i=1}^{n} z_i = 1 \text{ Proportions sum to unity}$$

$$DL_i \le z_i \le DU_i \forall i = 1 \ldots\ldots n \text{ Upper \& lower constraints on the policy variables}$$

where z_i is the targeted proportion of total expenditure for nationality i next period (the policy variable).

y_i is the forecast level of expenditure per bed night for nationality i next period.
b_i is the forecast level of bed-nights for nationality i next period with unchanged policies.
E is the specified expected level of expenditure, which is varied to generate the efficiency frontier.
σ_{ij} is the forecast covariance of expenditure by nationalities i and j, i.e. the covariances of y_ib_i and y_jb_j.
n is the number of nationalities.
DL_i is the non-negative lower bound on the policy variable for nationality i.
DU_i is the non-negative upper bound on the policy variable for nationality i.

3.3. Growth rates model (GRM)

The GRM is a different approach to optimizing the mix of tourist nationalities. The original formulation of the Markowitz portfolio theory in finance is mathematically equivalent to a GRM, where the aim is to allocate an arbitrary sum of money across financial assets with different returns (growth rates) to minimise the risk of a specified expected total rate of return (growth rate), e.g. *G* in equation (3), and so is scale independent. Accordingly, when applied in other contexts, such as devising optimal tourist market mixes to maximize international tourism revenue and stability, the implications from solving a GRM have a different meaning to those of Levels Model 1 and Levels Model 2. In addition, when applied to tourism, the GRM assumes there are no accommodation or transport capacity constraints on the total growth rate, which is unrealistic. The GRM can be used to optimise the expected growth rate of total tourist arrivals, bed-nights or expenditure, depending on the objectives of the destination's policy makers. The GRM for tourism, with upper and lower constraints on the policy variables, i.e. the *w*'s in equation (3), has been stated in the same form as the Markowitz portfolio model as:

$$\text{Min} \quad \Psi = \sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j \sigma_{ij} \text{ Minimise total expenditure growth rate risk} \tag{3}$$

$$\sum_{i=1}^{n} w_i g_i = G \text{ A specified total growth rate of total expenditure}$$

$$\text{subject to} \quad \sum_{i=1}^{n} w_i = 1 \text{ Proportions sum to unity}$$

$$GL_i \le w_i \le GU_i \forall i = 1 \ldots\ldots n \quad \text{Upper \& lower constraints on the policy variables}$$

where w_i is the target proportion of the growth rate of total expenditure who are of nationality i (the policy variable).

g_i is the expected growth rate of total expenditure by nationality i.
σ_{ij} is the covariance of the growth rates of total expenditure by nationalities i and j.
G is the specified expected growth rate of total tourist expenditure.
GL_i is the non-negative lower bound on the growth rates policy variable for nationality i.
GU_i is the non-negative upper bound on the growth rates policy variable for nationality i.

The policy variables of Levels Model 1 and Levels Model 2 have a clear meaning (i.e. the proportionate change in the level of bed-nights for each nationality, or the proportion of total expenditure for each nationality); but interpreting the meaning of the policy recommendations or managerial implications for destination marketers of the GRM presents some challenges. Previous researchers have interpreted the GRM policy variables as vague indications of directions of change. For example, Kennedy (1998, p. 123) has written that "we could interpret these weights as indications of the direction in which marketing funds should be allocated"; Chen, Jang & Chen (2011, p. 611) agree that "these weights are indications of the direction in which marketing funds should be allocated", and this latter interpretation is shared by Chen and Chen (2012).

There are two possible ways of converting the policy variables produced by the GRM into the implied changes in total expenditure by each nationality/national market. The first assumes that expenditure by each nationality increases at its forecast rate with unchanged policies. The difference between the increase in total expenditure implied by the specified total growth rate (i.e. $g\Sigma e_i$), where e_i is the current level of total expenditure for nationality *i;* and that produced by each nationality's expenditure increasing at its forecast rate ($\Sigma e_i g_i$), is then allocated across the nationalities in the proportions given by the policy recommendations of the portfolio solution (w_i). So the extra growth in expenditure allocated to nationality i is $w_i(g\Sigma e_i - \Sigma g_i e_i)$, and the total growth rate (expected growth plus growth due to policy) for nationality i is $[e_i(1 + g_i) + w_i(g\Sigma e_i - \Sigma g_i e_i)]/e_i$.

In the second interpretation, the specified increase in total expenditure ($g\Sigma e_i$) is distributed across the nationalities according to the policy variables (w_i). In this case the recommended increase in expenditure by nationality i is $w_i g\Sigma e_i$, which implies a growth rate in expenditure for nationality i of $[e_i + w_i g\Sigma e_i]/e_i$. The growth rate of total expenditure by a particular nationality using the second interpretation can be substantially different from that for the first interpretation.

Although the GRM allows negative growth for particular nationalities, sometimes a large negative policy recommendation implies negative tourist expenditure for a particular nationality, which is impossible. So, if the model does not already place an adequate lower bound on the policy variables, it needs to restrict each policy variable to rule out negative expenditure, i.e. $e_i(1 + g_i) + w_i(g\Sigma e_i - \Sigma g_i e_i) \geq 0$ for each nationality in the first interpretation, and $e_i + w_i g\Sigma e_i > 0$ for the second. Unless upper constraints are imposed on the policy recommendations for allocating the growth in total expenditure, they can also be large, offset by large negative policy recommendations for other nationalities, leading to unrealistically large changes in the total expenditure for these nationalities.

3.4. Comparison between the three models

In synthesis, the three models described above differ in this way: the Levels Model 1 maximises the level of total tourist expenditure, while minimising the variance of total tourist expenditure.

The Levels Model 2 also minimises the risk of total expenditure in terms of its standard deviation, with upper and lower constraints on the policy variables, but no upper constraints on total bed-nights or arrivals. The policy variables in the Levels 2 and Growth Rates models are defined in a different way to those in the Levels 1 model, as they are required to sum to one. The Growth Rates Model minimises the risk of total expenditure growth rate, with upper and lower constraints on the policy variables.

4. Data and methods

4.1. Data

We illustrate the differences in tourism policy recommendations and managerial implications for destination marketers between the three models by applying them to four destination countries: Australia, Greece, Japan and the USA. These four destination countries were chosen to provide examples of distinctively different types of tourism destination–- a large developed Western country (USA), a Western tourist destination country with a relatively large tourism industry (Greece), a developed Asian country (Japan) and an Asian country with a substantial immigrant population (Australia). They cover Western and Eastern destinations, as well as destinations located in the Northern and Southern hemispheres. To quantify the level of tourist activity in Levels Model 1 and Levels Model 2 we use bed-nights, rather than arrivals, because they are a better measure of accommodation capacity (e.g., Botti et al., 2012).

We analyse annual data for international bed-nights and expenditure per bed night from 2005 to 2019 (which is longer than most of the existing studies in tourism portfolio research) for the main tourist markets in four countries: 22 tourist markets for Australia (Australia Government, Tourism Research Australia, 2020); 19 tourist markets for Greece (Bank of Greece, 2020); 20 tourist markets for Japan (Japan Tourism Agency, Japan Tourism Statistics, 2020); 35 tourist markets for the USA (US Department of Commerce, National Travel and Tourism Office, 2020).[2] While these countries provide data on 19 to 35 nationalities, we have restricted our portfolio analysis to the nine nationalities with the highest expenditure in 2019. This is because the three models (Levels Model 1, Levels Model 2 and GRM) require estimation of a covariance matrix, and this is not possible when the number of nationalities exceeds the number of observations. To ensure that we consider 100% of international tourists, we group the smaller nationalities into a single group (Others). For the GRM this data was used to compute the growth rates of total tourist expenditure for each nationality. Table 2 summarises the data on the four countries.

Most of the previous portfolio studies have used annual data. Consistently with those studies, also our study uses annual data. For some countries such as Greece we have monthly data that allowed us to discover that the nationality mix does not vary by season in our sample.

4.2. Estimation of the portfolio inputs

When applying portfolio theory to financial assets, due to the evidence that these markets are weak efficient (i.e., the best predictor of future returns is the historic mean return), the mean of the historic returns is generally used to estimate the expected asset return next period. But this reasoning does not apply to tourism bed-nights or expenditure. Unlike financial markets, past changes in bed-nights or tourist expenditure can be used to predict future changes in these variables. Thus, we estimate time series regression models for bed-nights and expenditure per bed night for each nationality/tourist market to forecast their values next period with no change in policy. Changes in the factors which affect tourism by each nationality (e.g., taste and fashion, political unrest, terrorism, epidemics, exchange rates, incomes,

Table 2
Descriptive statistics for the four countries: 2005–2019 – per year.

	Average Total Bed-nights	Average Total Expenditure	Average Total Expenditure per Bed-night
Australia	65 mn.	A$7074 mn.	A$109
Greece	173 mn.	€12,518 mn.	€72
Japan	75 mn.	¥168,633 mn.	¥22,480
USA	539 mn.	$82,359 mn.	$153

[2] The previous literature has measured the level of tourist activity in one of three ways - tourist arrivals, tourist bed-nights and tourist expenditure. We argue that the level of bed nights is superior to using arrivals as tourist length of stay differs by nationality and relates directly to tourist accommodation capacity. We then multiply the number of bed nights by expenditure per bed night as this also differs by nationality, and is a measure of the economic impact of tourism.

marketing expenditure and transport and accommodation facilities and prices) are hard to predict. They represent exogenous shocks which will probably continue to occur in an unpredictable manner, and we treat them as risks in the portfolio models that are incorporated in the estimated variances and covariances, rather than allow for them explicitly in the time series regressions.

To estimate the expected number of bed-nights, expenditure per bed night and growth rate of total expenditure in 2020 for each nationality we employ Least Absolute Shrinkage and Selection Operator regression (LASSO) to improve the predictive accuracy of our estimates (Tibshirani, 1996). LASSO is a regularization method that avoids overfitting issues, which enables it to be applied when there is a small number of observations. For a sample consisting of M cases, and for p regression coefficients, β_j, the general idea of the LASSO regression is to minimise the sum of the squared residuals subject to a penalty via a l_1-norm. Its functional form is given by:

$$L(\beta,\theta)=\sum_{t=1}^{M}(y_t-\beta_0-\sum_{j=1}^{p}\beta_j x_{jt})+\theta\sum_{j=1}^{p}|\beta_j| \; . \tag{4}$$

where x_{jt} is the j^{th} regressor at time period t, and $\theta \geq 0$ denotes the penalizing parameter. The LASSO regression reduces to OLS when $\theta = 0$. When $0 < \theta < \infty$, LASSO eliminates all irrelevant variables (lags in our case) by shrinking their coefficients (β_j) to zero. To estimate (forecast) bed-nights, expenditure per bed night and growth rate of total expenditure in 2020, we implement LASSO in MATLAB, which uses a geometric sequence of θ values to find the optimal solutions that corresponds to the minimum cross-validated mean squared error (MSE). We use up to five lags ($p = 5$) and LASSO, due to its shrinkage nature, shrinks the weights of any redundant (irrelevant for forecasting) lags to zero.

Some applications of portfolio theory to regional economies have used Sharpe's single index model (Sharpe, 1963) to estimate the covariances between the various industries in the region, but this is inappropriate for tourism as there is no obvious index. So, for Levels Model 1 and Levels Model 2 we estimate the annual covariances of total expenditure by each nationality using their historic values. For the GRM we estimate the covariances of the growth rates using the historic growth rates of total expenditure for each nationality/tourist market.

Every destination has a capacity constraint and, as it is uneconomic to have unused capacity, tourist destinations tend to operate at or near their capacity. Levels Model 1, Levels Model 2 and the GRM treat capacity as a hard constraint that must be met, but capacity can be treated as a soft constraint, and various approaches exist for modelling soft constraints in portfolio models. The use of a penalty function allows the constraint to be breached at a cost measured in terms of the units of measurement of the objective function, which now includes the penalty function. A slightly different formulation is that meeting the constraint is included in the objective function as another goal using either lexicographic goals or weighted goals. Alternatively, the size of the constraint may viewed as probabilistic, and this can be tackled using chance constrained or stochastic programming.

Very large values of the policy variables are unrealistic, and negative values are impossible; therefore, some constraint on the magnitude of annual changes that can be achieved by tourism policy interventions or destination marketing strategies is required. Previous annual values of the policy variable have been caused by both policy interventions and exogenous events; therefore, past values of the policy variable are an overestimate of what is achievable by just policy interventions. Assuming the values of the policy variables have a normal distribution, we set the constraints to permit 95% of previous annual values of the policy variable, which corresponds to the 5% confidence level commonly used in significance tests. The size of the upper and lower constraints is not crucial to our conclusions. For Levels Model 1 this is two standard deviations above (AU_i) and below (AL_i) their historic level of bed-nights. For Levels Model 2 the constraints (DL_i and DU_i) on the policy variables for each nationality are two standard deviations above and below their historic shares of total expenditure. Similarly, using the second interpretation of the GRM policy variables, we set the upper (GU_i) and lower constraints (GL_i) on the policy variables for each nationality at twice the standard deviation of the shares of the change in total expenditure.

5. Findings

Using MATLAB and the values estimated in section 4 as inputs, we solved Levels Model 1, Levels Model 2 and the GRM using 4000 different values of E and G between the highest and lowest values that produced a solution for each of the four destination countries. We also solved these models using the Black-Litterman (Black & Litterman, 1992) portfolio model. This is a popular method for dealing with estimation risk in the input parameters that combines the decision maker's subjective estimates of the 'expected returns' (views) with a reference portfolio of policy weights. The policy weights for our four example countries computed using the Black-Litterman model are identical to those of the three models described above, largely due to the imposition of the upper and lower constraints; indicating that the use of sophisticated portfolio modelling that allows for estimation risk offers no benefit in this case.

For each of the three models (Levels Model 1, Levels Model 2 and GRM) and four example destination countries (Australia, Greece, Japan, USA), we compute the efficient frontiers. For each level of total expenditure or growth rate, Figs. 1–12 plot the lowest standard deviation of total expenditure or growth rate from the possible portfolios of tourists computed by each portfolio model.

All these efficiency frontiers have the expected shape of a convex function. However, in Fig. 3 only the portion of the efficiency frontier where total expenditure and risk are both increasing is worth considering, as destinations would not choose portfolios with both higher risk and lower expenditure. For low values of total expenditure, the frontier can slope up to the left at an increasing rate until the minimum variance portfolio is reached. The frontier then slopes up to the right at a decreasing rate, and this part of the frontier dominates the part that slopes up to the left.

In the Levels Model 1 and Levels Model 2 figures we have also plotted the existing solution in 2019 (denoted K).[3] Since the solution in 2019 is a level, K is not plotted in the GRM figures. These figures show that the existing solutions (point K) plot well within the Levels Model 1 frontier, indicating that substantial improvements in the tourist market mix are possible for all four destination countries. Given the level of returns for the existing portfolios (K) for the Levels Model 1, the corresponding portfolios on the efficient frontiers offer reductions in the variances of returns of 40% for Australia, 54% for Greece, 86% for Japan and 61% for the US.

Substantial policy improvements are also indicated by Levels Model 2 for Australia and the USA, although only small improvements are available for Greece and Japan. Overall, all three models (Levels Model 1, Levels Model 2 and GRM) generate what look to be sensible solutions that appear to be implementable by policy makers, apparently leading to improvements in performance. However, this conclusion is incorrect because all the Levels Model 2 and GRM solutions breach the total bed-nights constraints.

In Figs. 13–16 we plot total bed-nights against total expenditure for the three models and four example countries. The horizontal threshold lines represent the total bed-nights constraint, and any solution that plots above these lines is infeasible. Figs. 13–16 show that all the Levels

[3] The values of K for the LM1 and LM2 models differ as these two models define the policy variable differently. For LM1 x_i is the targeted proportionate change in the level of bed-nights for nationality i next period, i.e. the level of operation for each tourist nationality. For LM2, z_i is the targeted proportion of total expenditure for nationality I next period.

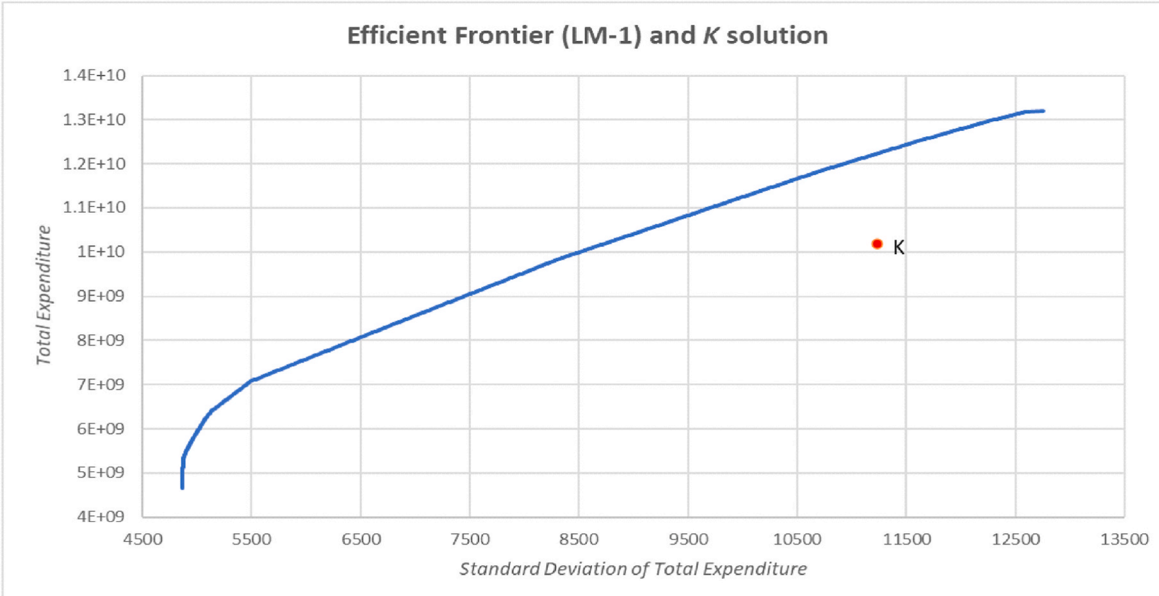

Fig. 1. Australia – Total Expenditure and Standard Deviation of Total Expenditure - Levels Model 1 Efficient Frontier. K = existing solution.

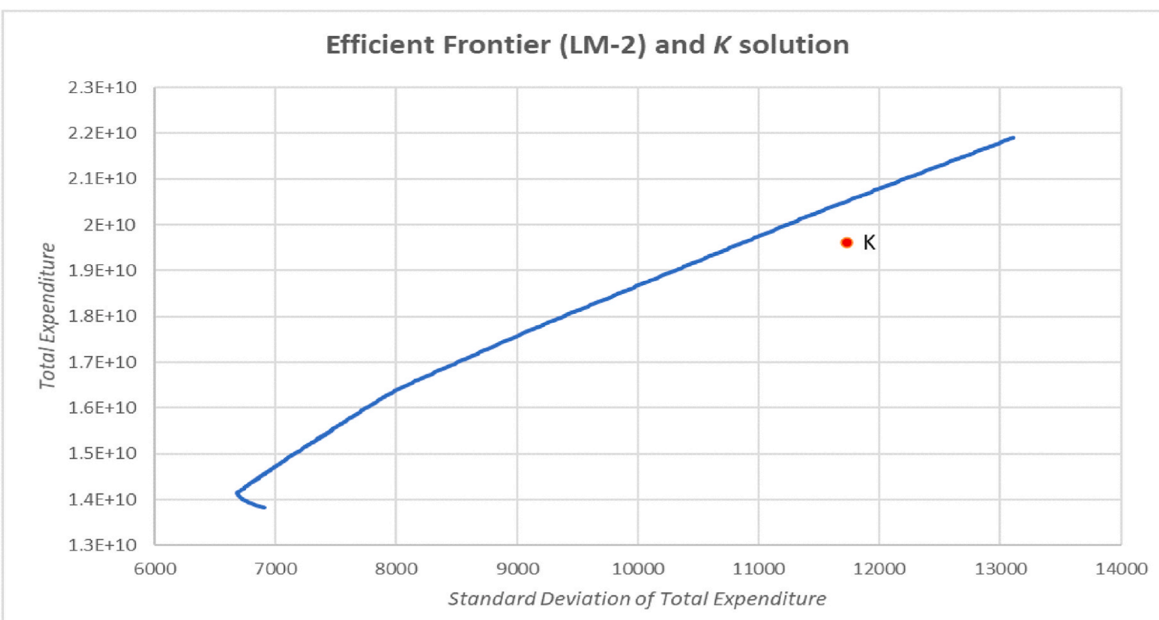

Fig. 2. Australia – Total Expenditure and Standard Deviation of Total Expenditure - Levels Model 2 Efficient Frontier. K = existing solution.

Model 2 and the GRM solutions lie completely above this threshold, with some solutions requiring three times the available bed-nights. Therefore, none of the Levels Model 2 and GRM solutions can practically be implemented by tourism policy makers or destination marketers. In contrast, all of the Levels Model 1 solutions are feasible. For higher levels of total expenditure, the total bed-nights constraint is binding, and this can be seen in Figs. 13–16 where the Levels Model 1 efficient frontier becomes a flat line that runs along the threshold. So, while Levels Model 1 produces implementable solutions which will result in improved performance, the Levels Model 2 and the GRM are inappropriate, as they provide apparently plausible results offering performance improvements that cannot be achieved.

6. Discussion, theoretical contributions and practical implications

6.1. Discussion and theoretical contributions

Our study makes several important theoretical and methodological contributions to the research stream of tourism portfolio models. First, we suggest that portfolio theoretical development in the context of tourist market mixes should focus on Levels Model 1 models, in keeping

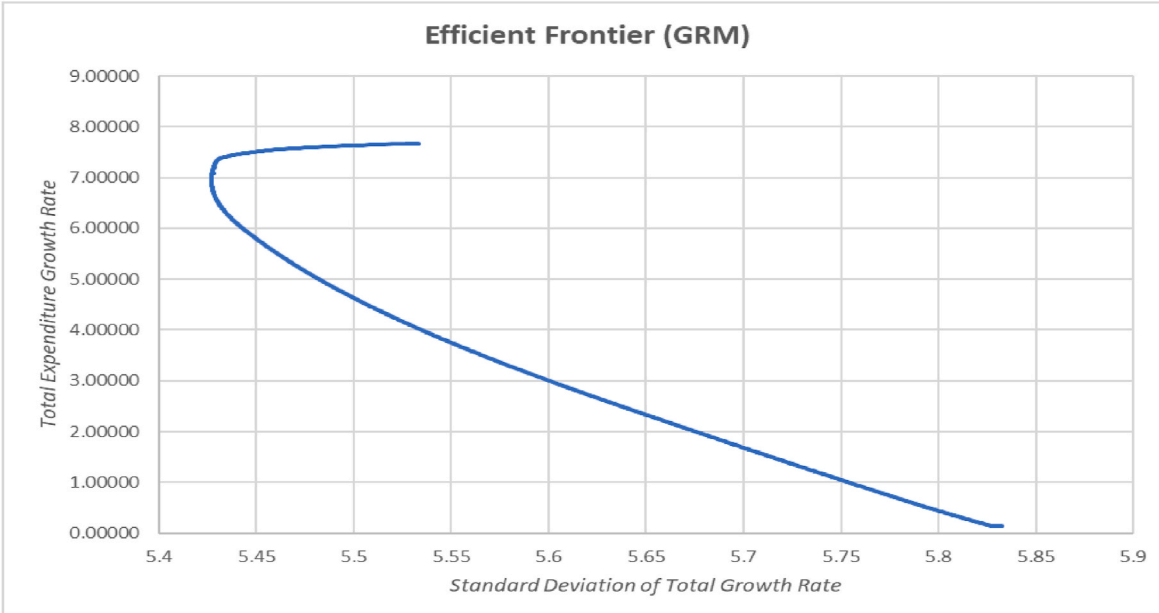

Fig. 3. Australia - Total Expenditure Growth Rate and Standard Deviation of the Growth Rate - GRM Efficiency Frontier.

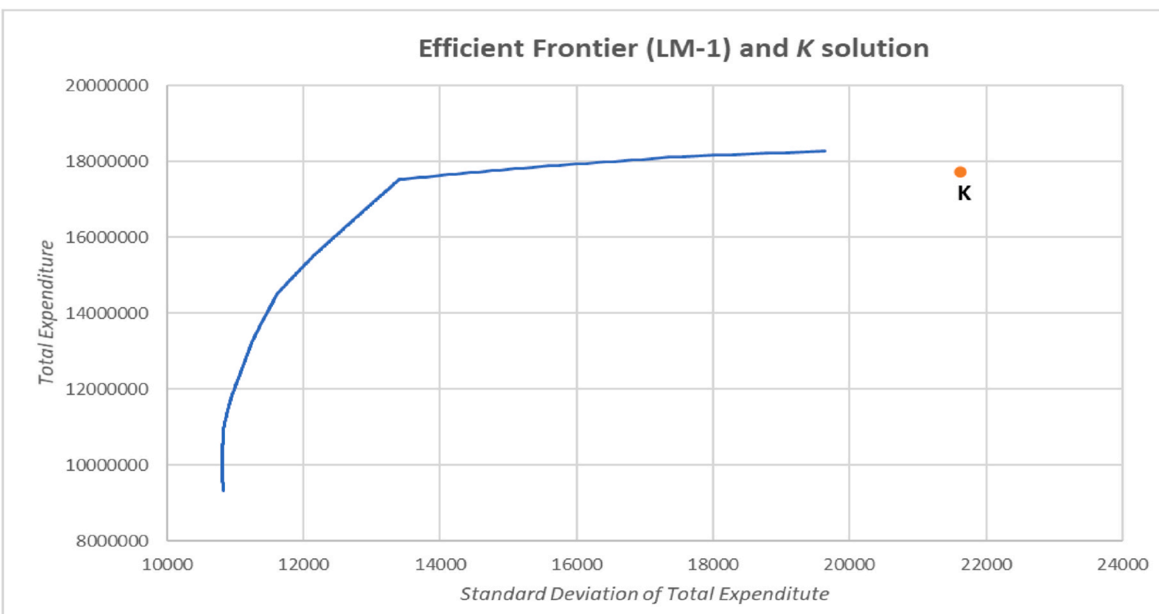

Fig. 4. Greece – Total Expenditure and Standard Deviation of Total Expenditure - Levels Model 1 Efficient Frontier. K = existing solution.

with the tradition of studies that have used this type of model (Board et al., 1987; Board & Sutcliffe, 1991; Sinclair, 1999). As is shown by our empirical analysis of four example countries, Levels Model 1 generates implementable solutions which result in improved performance, whereas the Levels Model 2 and GRM solutions are inappropriate and their solutions are unimplementable. More generally, these findings contribute to tourism management research by suggesting that tourism researchers have misused several models (Levels 2 and GRM) for a number of reasons, including mistakes or omissions in model specifications and therefore they should stop using the Levels 2 and GRM models.

Second, the Levels Model 1 and Levels Model 2 are static, scale dependent, models which optimise the tourist mix to minimise the risk for a specified level of total tourist accommodation, and do not consider its rate of growth. If desired, they can analyse the effects of growth in the size of the tourist industry, e.g. the effect of bed-nights on the optimal mix of nationalities by increasing the specified total accommodation capacity. The GRM minimises the risk of variations in the growth rate of total expenditure for a specified total growth rate. It does not consider the levels of expenditure by the various nationalities, and so changing the forecast levels of expenditure for each nationality has no effect on the policy recommendations. This is inconsistent with the goal of

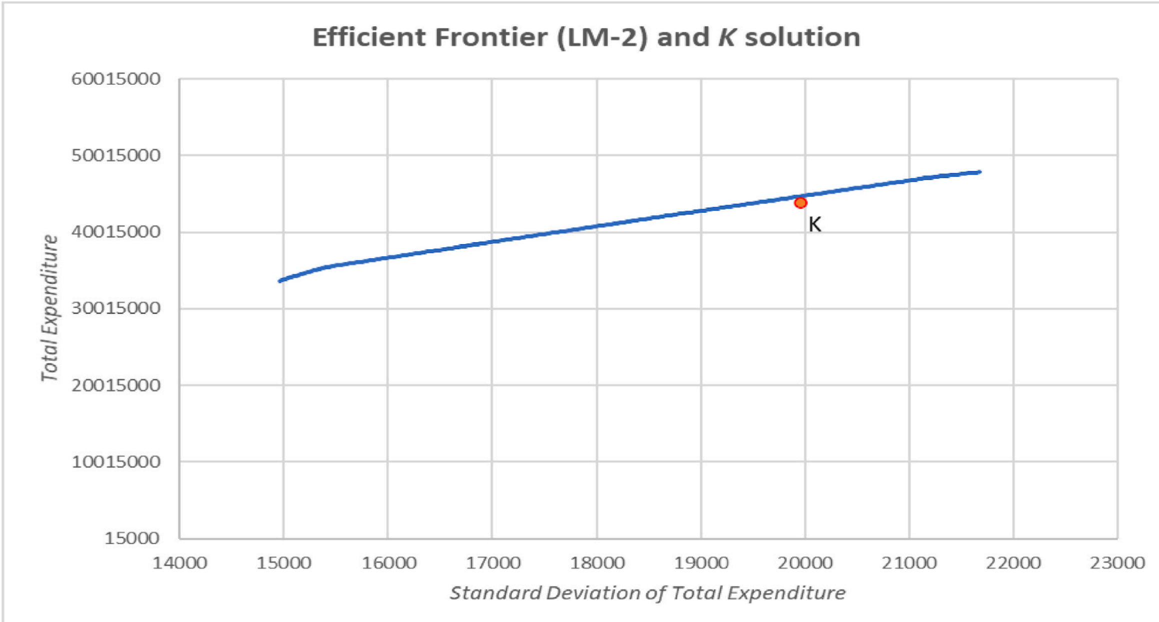

Fig. 5. Greece – Total Expenditure and Standard Deviation of Total Expenditure – Levels Model 1 Efficient Frontier. K = existing solution.

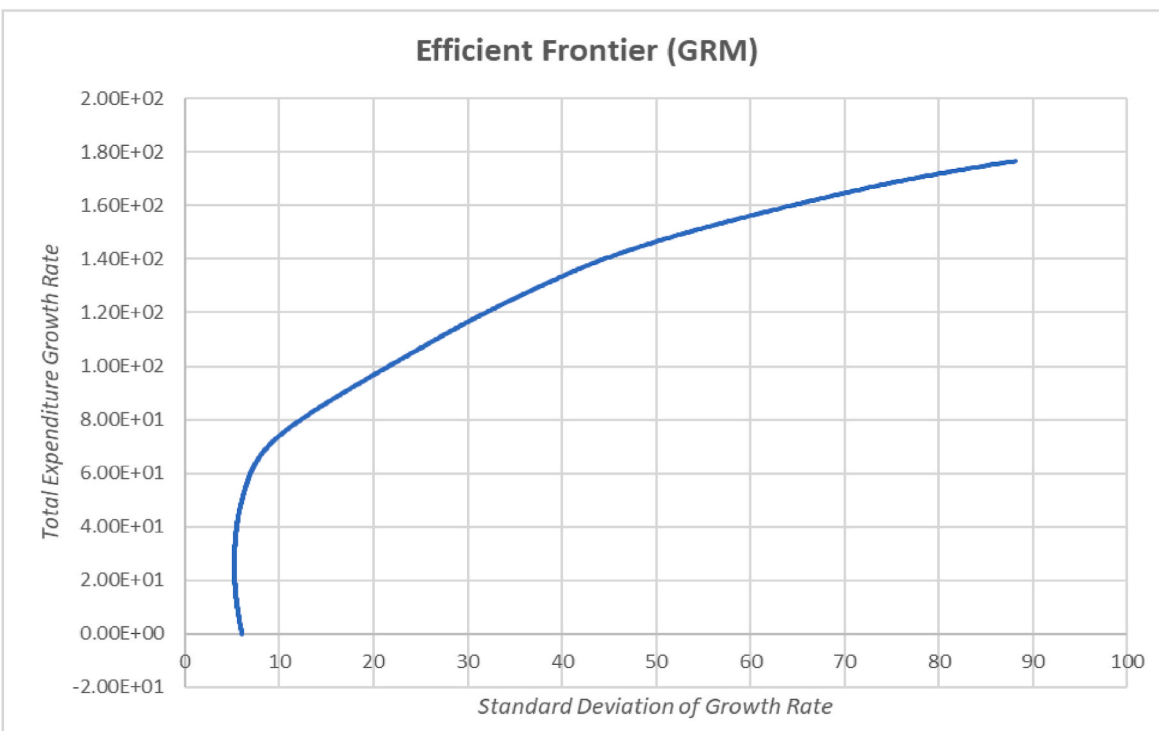

Fig. 6. Greece - Total Expenditure Growth Rate and Standard Deviation of the Growth Rate - GRM Efficiency Frontier.

maximizing tourist revenues. This is not the case for Levels Model 1 and Levels Model 2, where differences in the level of tourist expenditure between countries ($y_i b_i$) lead to substantially different policy recommendations. The GRM uses the forecast growth rates of expenditure for each nationality as parameters of the model, and these are scale independent. Because there are substantial differences in the level of total expenditure between nationalities, minimising the variability of total expenditure is not the same as minimising the variability of the growth rates of total expenditure. The afore-mentioned considerations inform all the previous tourism portfolio literature (e.g., Ivanovic et al., 2018; Rakotondramaro & Botti, 2018; Sinclair, 1999).

Third, and in relation to the previous point, we offer an explanation and demonstration of the different nature of the three models using the differences in the inputs of the levels and growth rates models. The time

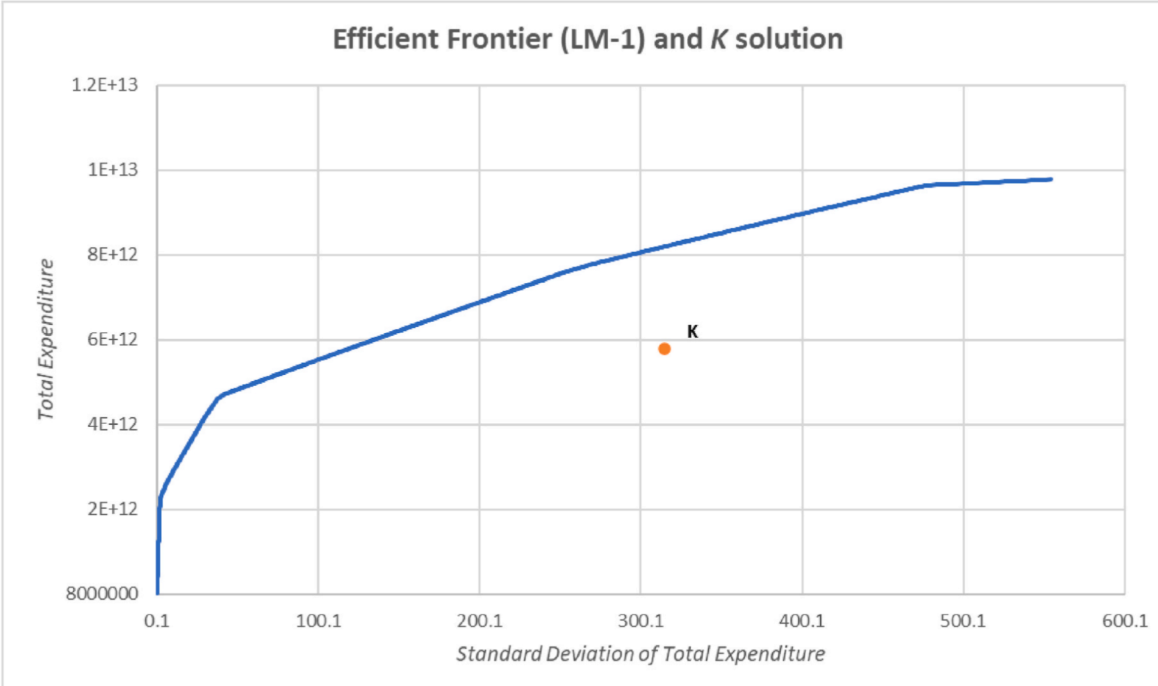

Fig. 7. Japan – Total Expenditure and Standard Deviation of Total Expenditure - Levels Model 1 Efficient Frontier. . K = existing solution.

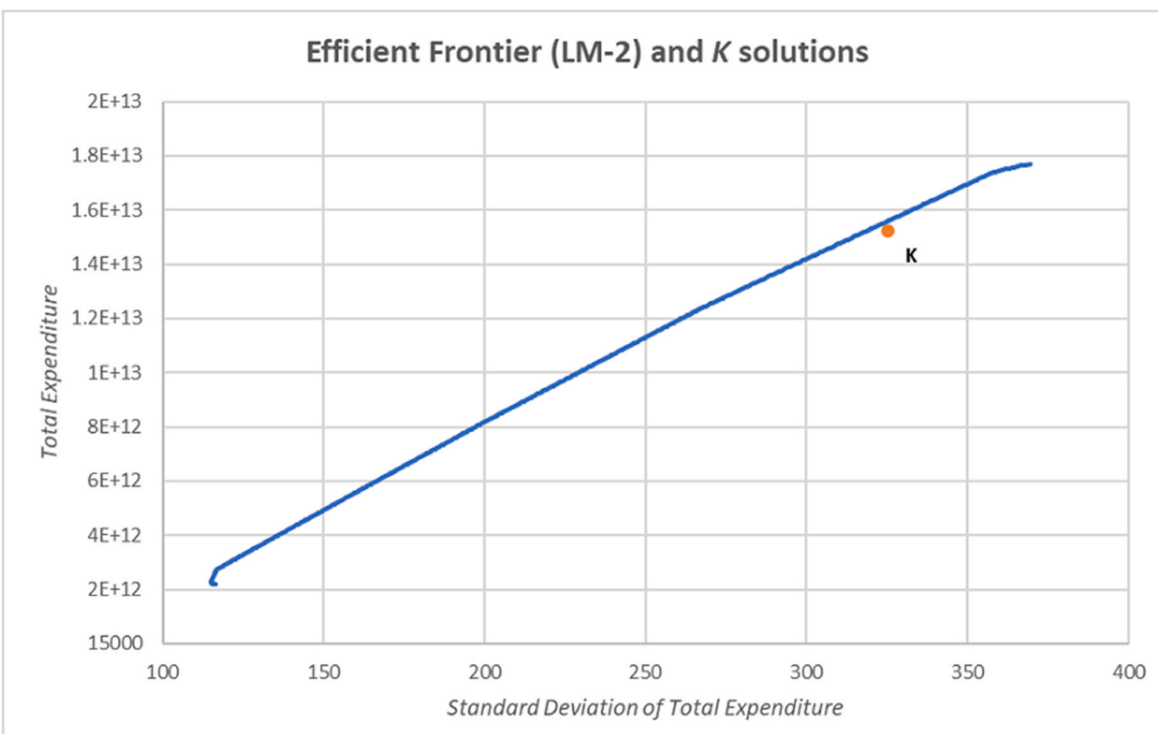

Fig. 8. Japan – Total Expenditure and Standard Deviation of Total Expenditure - Levels Model 2 Efficient Frontier. K = existing solution.

series of the levels of tourist expenditure by any nationality (L_0, L_1, L_2, L_3, … L_n) can be rewritten as $L_0\{(1, (1+g_1), (1+g_1)(1+g_2), (1+g_1)(1+g_2)(+g_3), \dots (1+g_1)(1+g_2)(+g_3) \dots .(1+g_n)\}$, where g_t represents the growth rate for period t. Letting $M_{t=0}^{n} a_t$ represent the series a_0, a_0a_1, $a_0a_1a_2$, $a_0a_1a_2a_3$, ….. $a_0a_1a_2a_3 \dots a_n$, the means and variances of the time series of expenditure by a nationality for the two model formulations

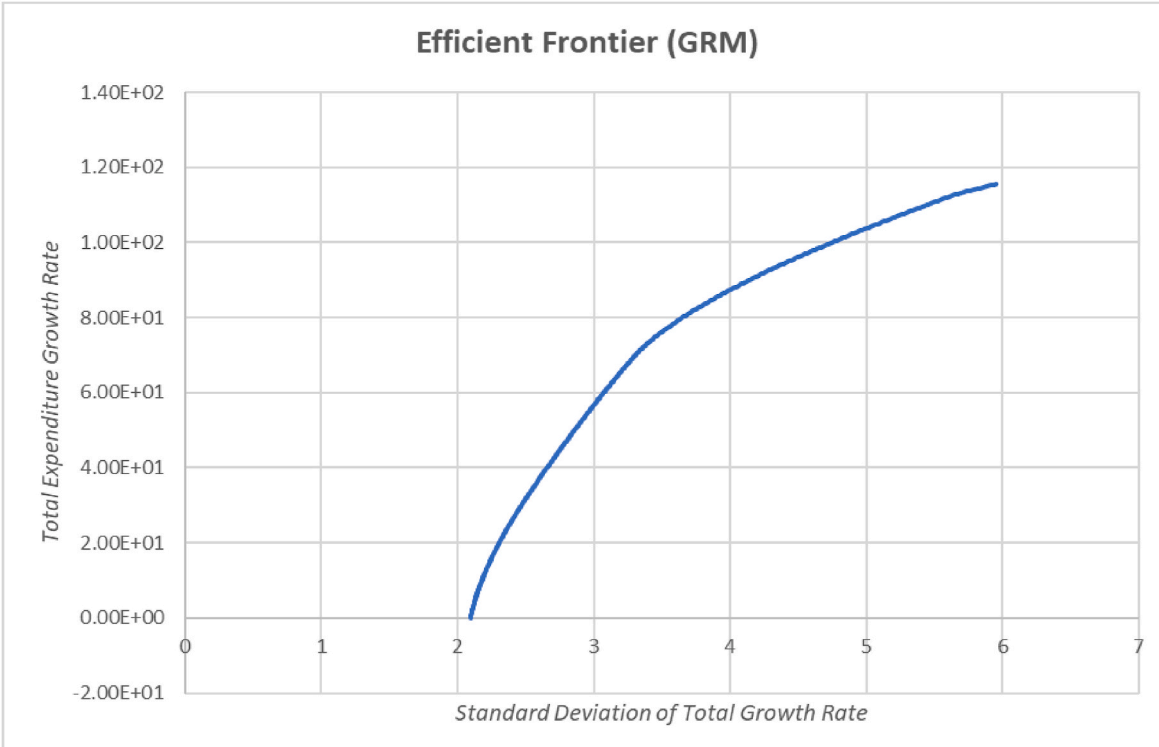

Fig. 9. Japan - Total Expenditure Growth Rate and Standard Deviation of the Growth Rate - GRM Efficiency Frontier.

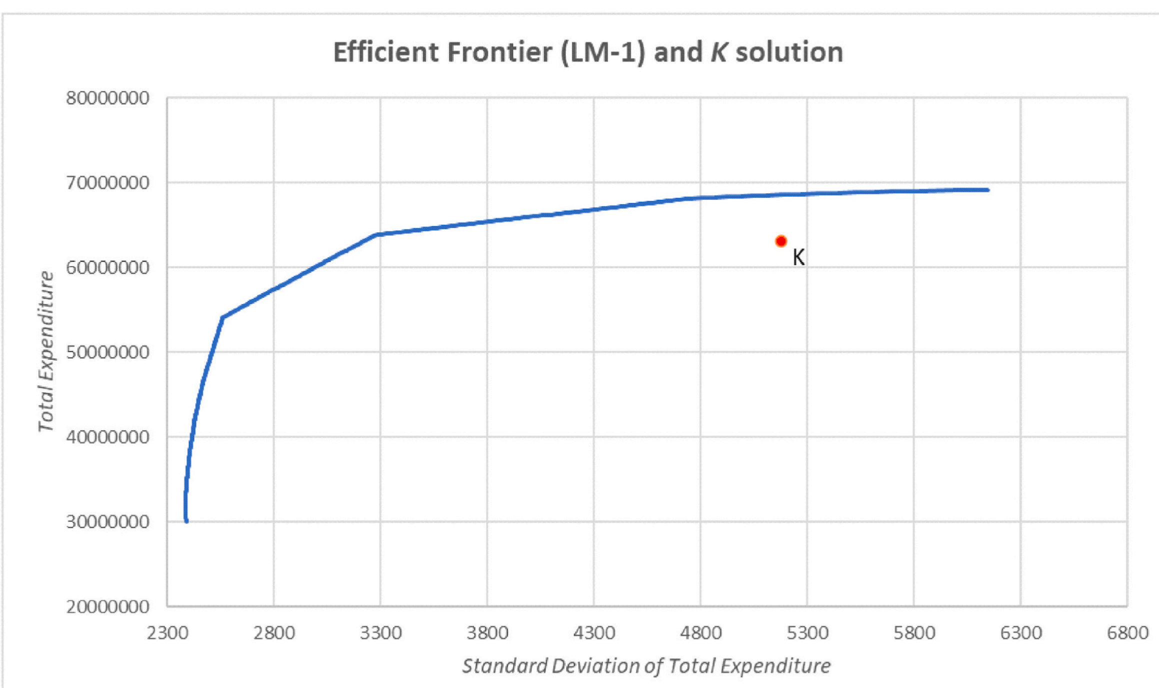

Fig. 10. USA – Total Expenditure and Standard Deviation of Total Expenditure - Levels Model 1 Efficient Frontier. K = existing solution.

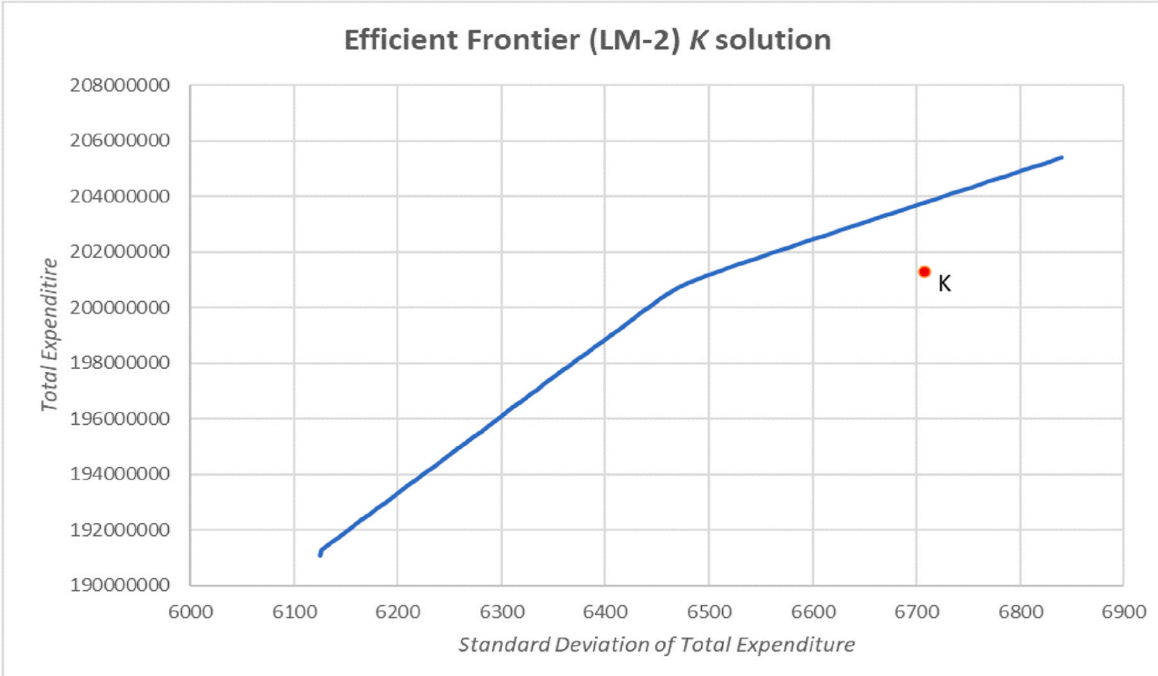

Fig. 11. USA – Total Expenditure and Standard Deviation of Total Expenditure - Levels Model 2 Efficient Frontier. K = existing solution.

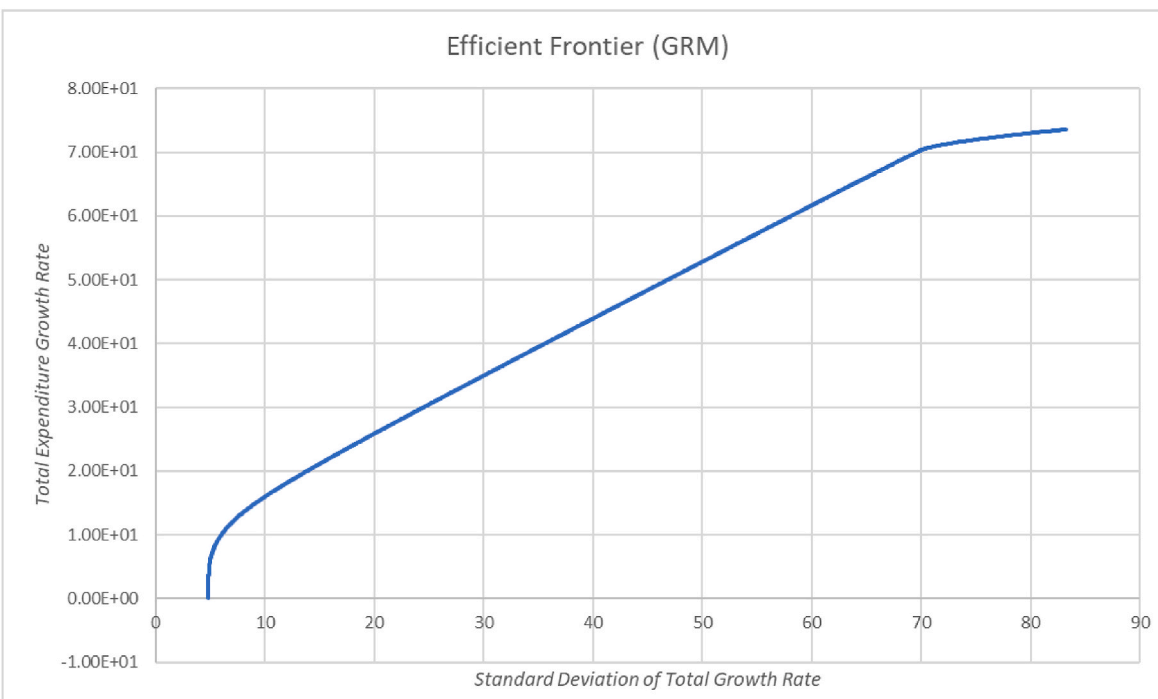

Fig. 12. USA - Total Expenditure Growth Rate and Standard Deviation of the Growth Rate - GRM Efficiency Frontier.

are:

Levels Models $\quad \text{Mean level} = \mathrm{L}_0 \sum_{t=0}^{n} \mathrm{M}_{t=0}^{n}(1+\mathrm{g}_t)\,/\,\mathrm{n}$

$$\text{Variance of levels} = \mathrm{L}_0{}^2 \mathrm{Var}\{\mathrm{M}_{t=0}^{n}(1+\mathrm{g}_t)\}$$

Growth Rates Model $\quad \text{Mean growth rate} = \sum_{t=0}^{n}(1+\mathrm{g}_t)\,/\,\mathrm{n}$

$$\text{Variance of growth rates} = \mathrm{Var}(1+\mathrm{g}_t)$$

Since the level of expenditure (L_t) only appears when computing the mean and variance for Levels Model 1 and Levels Model 2, and not the GRM, only Levels Model 1 and Levels Model 2 are affected by differences in expenditure between nationalities. Even if all nationalities currently have the same level of expenditure (L_0), the differences in the means and variances in the above equations which use historical values show that the levels model and GRM formulations have very different inputs. This

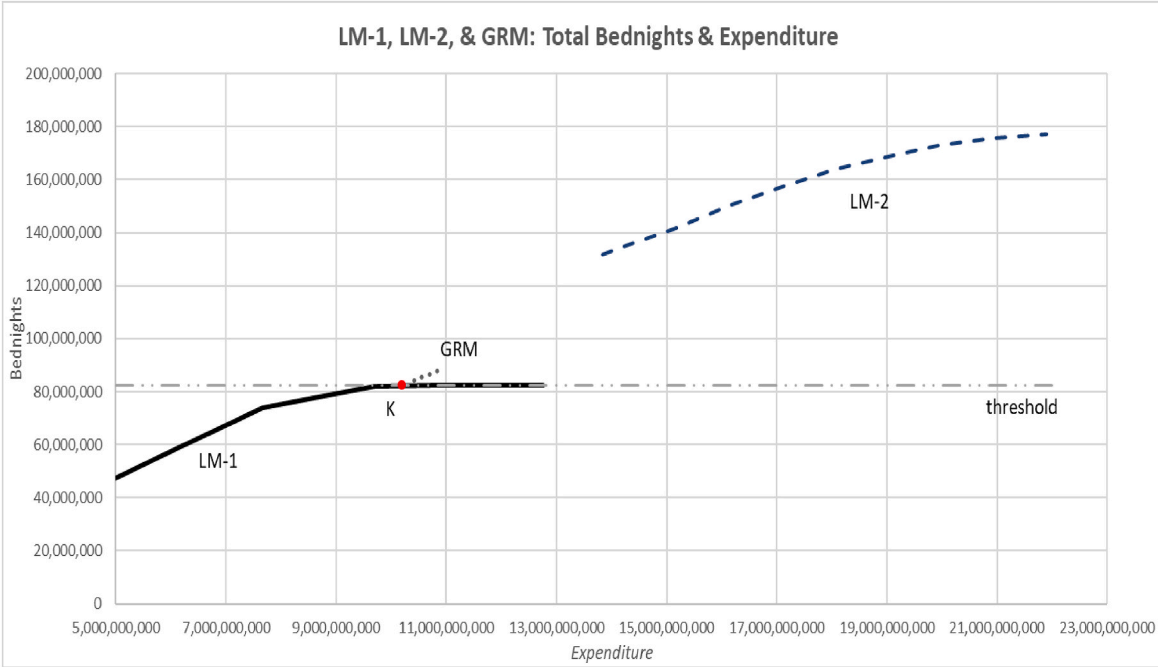

Fig. 13. Australia - Total Bed-nights and Total Expenditure for Levels Model 1, Levels Model 2 and GRM

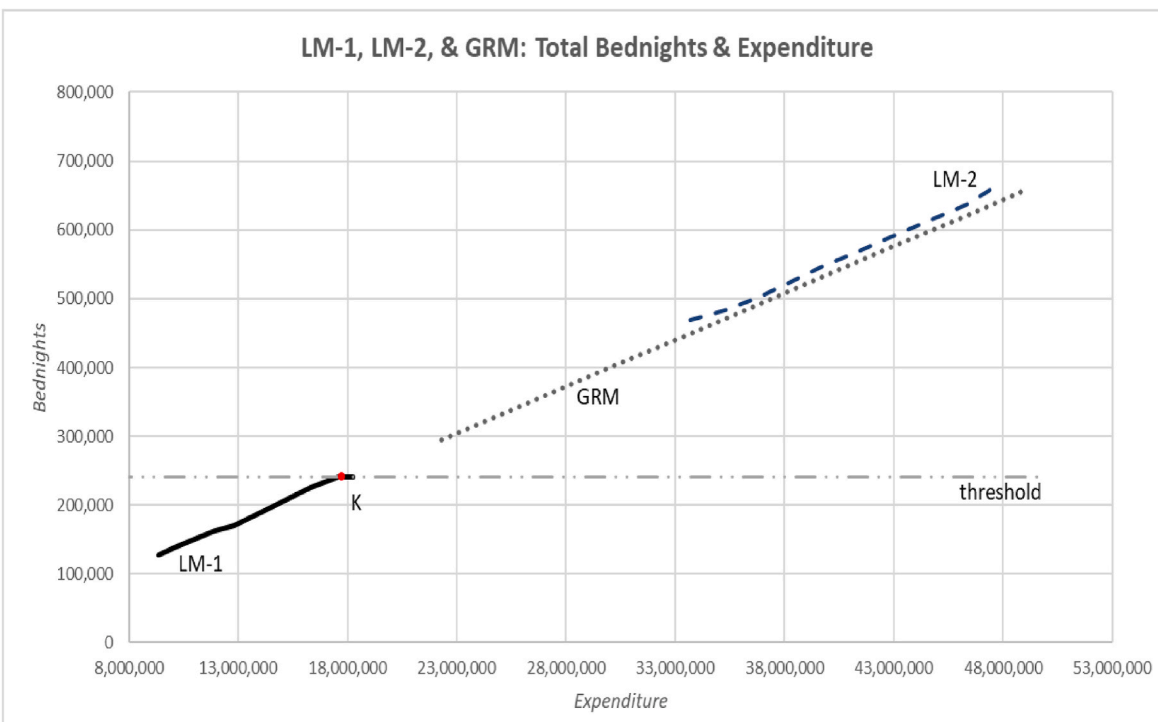

Fig. 14. Greece – Total Bed-nights and Total Expenditure for Levels Model 1, Levels Model 2 and GRM

demonstrates that these two formulations model different things, leading to different policy proposals.

Last, from a methodological point of view, we investigate whether the application of a more sophisticated type of portfolio model (i.e., the Black-Litterman) changes the available trade-offs between total tourist expenditure and its variability, and the underlying mixtures of tourist nationalities.

6.2. *Practical implications for policy makers and destination marketers*

This study has important practical implications for tourism policy makers and destination marketers. First, in choosing to target a particular mixture of tourist markets, tourism policy makers, and especially destination marketers of national DMOs, face a “risk-return” trade-off; i.e. accepting more instability and variability in total tourist expenditure in return for a higher level of expected total tourist expenditure.

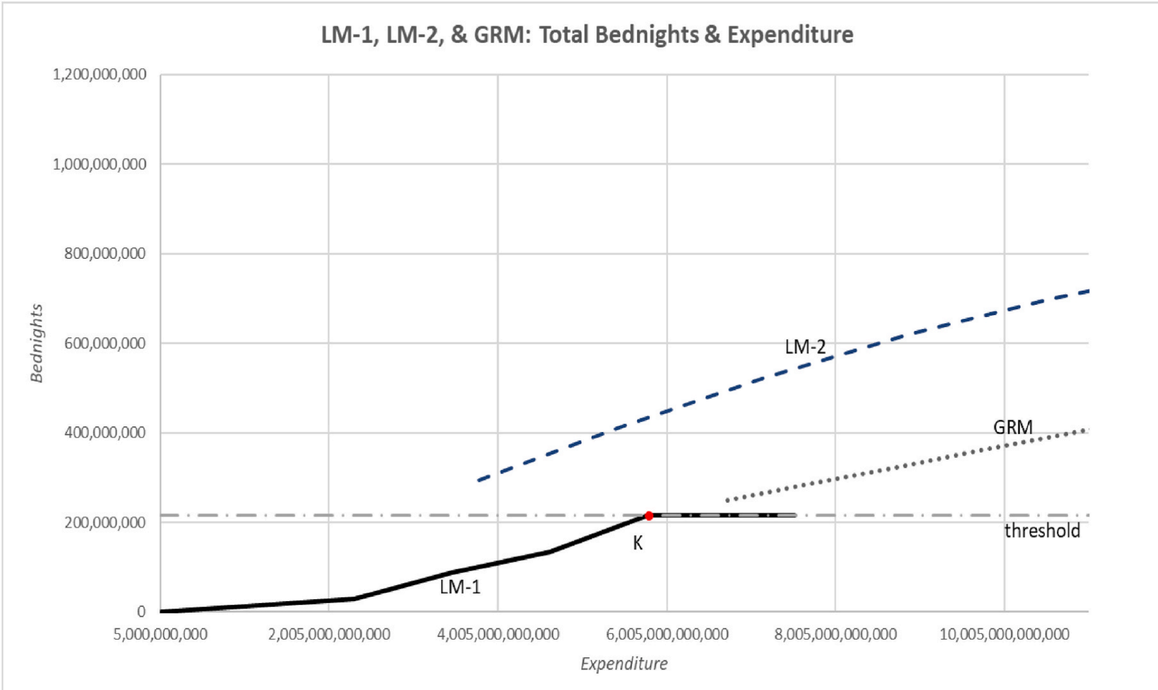

Fig. 15. Japan - Total Bed-nights and Total Expenditure for Levels Model 1, Levels Model 2 and GRM

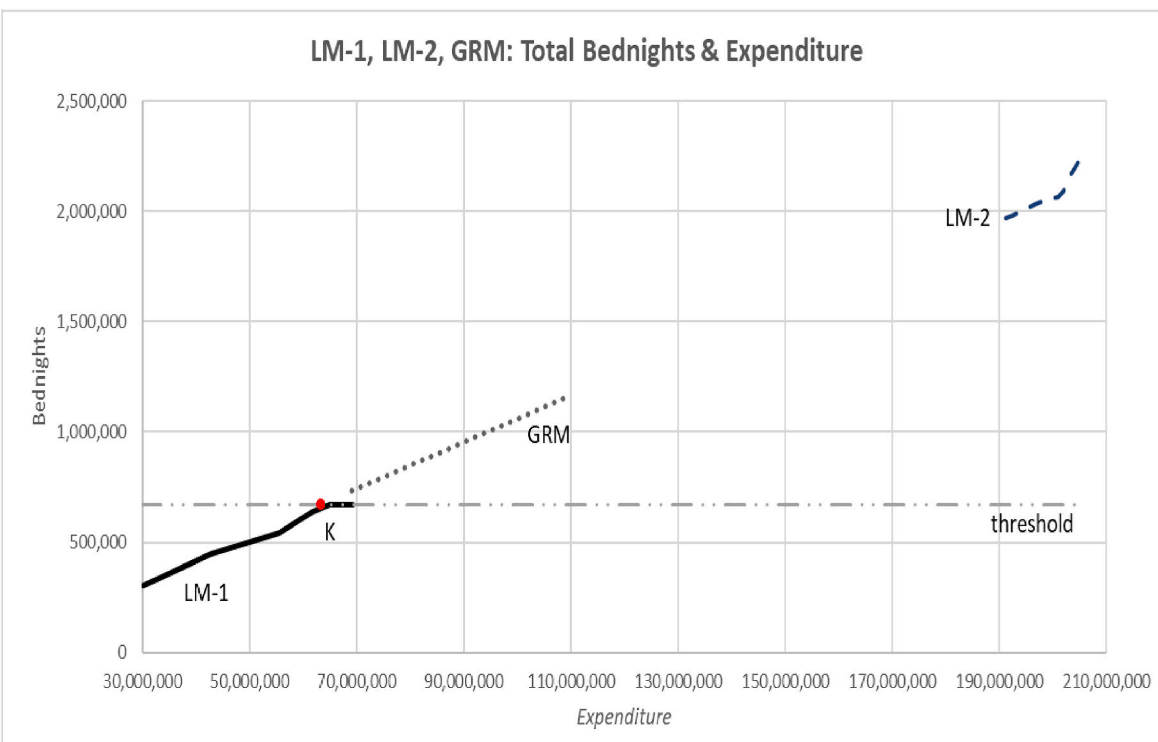

Fig. 16. USA - Total Bed-nights and Total Expenditure for Levels Model 1, Levels Model 2 and GRM

Therefore, tourism policy makers and destination managers can implement policies and strategies designed to change a destination's mixture of tourist markets, e.g., altering their marketing strategy and expenditure and developing particular types of tourist facilities. More specifically, destination managers and marketers might develop strategic marketing plans that could be translated into different combinations of the eight components – the so called 8Ps - of a destination marketing mix (Morrison, 2019), so that the marketing mixes can be customized based on the national market targeted. For instance, destination managers and marketers can: 1) affect the development of attractions, facilities and infrastructure that are particularly attractive for specific national groups, and lobby for the improvement of transport links with target origin countries; 2) influence the prices of the attractions charged to tourists based on their country of origin; 3) differentiate promotional efforts (in the form of advertising, personal selling at travel and tourism expos, PRs and digital communication) based on the target origin countries; 4) support the packaging activities of travel intermediaries that work with specific target origin countries; 5) shape their programs by setting up events and festivals that might be more appealing to one national group than another; 6) set up partnerships with other DMOs or incoming travel intermediaries with preferred origin countries; 7) recruit and retain talented personnel that can speak the language and understand the culture of a specific national group to improve those tourists' satisfaction with their trip. Tourism policy makers can: 1) work on regulations and laws to generate incentives for specific national groups; 2) waive visas for specific national groups); 3) generate incentives for travel intermediaries catering their packages to specific targeted national markets.

The three portfolio models could easily be modified by the inclusion of income multipliers for each nationality, and re-stated using a different disaggregation of tourists, e.g. age, gender, purpose of stay, length of stay, type of accommodation, mode of transport, environmental impact, etc.

Second, as tourism policy makers and destination marketers of national DMOs wish to improve the performance and competitiveness of their destinations (Crouch & Ritchie, 1999; Crouch, 2011(Mariani, Bresciani, & Dagnino, 2021)), they should make a careful decision in relation to the model they use to determine the optimal mixture of tourist markets. The objective of the two levels models (Levels Model 1 and Levels Model 2) is more appropriate for a destination's policy makers and destination marketers; as the two models allow for differences in scale between the different nationalities, and provide solutions that enable clear policy or strategy recommendations.

Third, when it comes to choosing between the level models (Levels Model 1 and Levels Model 2) our findings show that tourism policy makers and destination marketers should opt for the Levels Model 1 as it generates implementable solutions which will eventually result in improved performance. Accordingly, it is important that tourism policy makers and destination marketers use the only version of the portfolio model that produces feasible and efficient answers (Levels Model 1). The other models are inappropriate as, while they generate conventional efficiency frontiers, but their implementation is generally impossible. Tourist policy makers and destination managers who choose not to target an optimal tourist market mix, or who do so using a flawed model, potentially sacrifice both tourist income and a reduction in its variability.

7. Conclusions

After reviewing the body of travel and tourism literature on tourism portfolio models, this study has compared the three different types of portfolio model - Levels Model 1, Levels Model 2 and the GRM. The solutions of the two levels models have a straightforward interpretation, while the GRM solutions do not; and overall the Levels Model 1 is superior to the other two models. To illustrate our conclusions, we applied the three models to distinctively different destination countries - Australia, Greece, Japan, and the USA. Our findings are consistent across these four destinations, supporting the generalizability of our conclusions, which hold irrespective of the characteristics of the tourism destination considered - Western (USA) and Eastern (Japan) tourism destination countries, or destination countries in the Northern or Southern hemisphere (e.g., Japan and Australia), as well as countries whose GDP is largely reliant on tourism (e.g., Greece), and destinations with a high share of immigrants (e.g., Australia).

This study has a few limitations that are also opportunities for further research. First, unlike all the previous studies that focused on one destination country only, we purposefully collected data from four distinctively different destination countries (Australia, Greece, Japan, and USA) to prove that our findings are generalizable beyond a specific destination country. The choice of countries is appropriate and does provide a variety of different contexts to show that the portfolio selection approach can be used in the East or the West; and both in the Southern and Northern hemispheres, and that the findings hold regardless of the destination chosen. Practical reasons prevented us from enlarging further the sample given that: 1) it is very time consuming to collect the type of data needed for the study from additional destination countries; 2) there are page and word limitations that make it unfeasible to show all the efficient frontiers and solutions (at least four figures per country). This would drastically lengthen the manuscript without adding value. That said, we believe that our findings hold for any destination for the reasons explained in the discussion. Future research might collect data from additional countries to further corroborate the external validity and generalizability of our findings. Second, while our data relate to the pre-COVID period, the findings of this analysis are relevant for tourism destinations in the context of the ongoing COVID-19 pandemic. While in the short-term travellers' behaviour has shifted toward domestic and trusted destinations, experts forecast that international tourism should be back to its pre-COVID level by the end of 2023 (UNWTO, 2021). This implies that both tourism policy makers and destination managers – as well as tourism firms – should prepare to resume their activities and should forecast them (Atsalakis et al., 2018). When international tourism resumes, a rapid acceleration of international travel will take place in tandem with an increasing level of competition to attract international tourism flows. Consequently, our results offer guidance to both tourism policy makers and destination managers and marketers interested in revamping international tourism during and post the COVID-19 pandemic. Using the superior Levels Model 1 model to identify the tourist market mix will be important, especially for international tourism-dependent destinations or emerging tourism destinations. It will enable them to gain a competitive edge by minimising the instability of international tourism expenditure, while also maximizing international tourist expenditure.

These portfolio models have two goals – maximize total expenditure (return) and minimise its variability. In this new post COVID-19 setting, portfolio models could incorporate a third goal - to minimise some measure of the public health risk generated by tourists from different countries. Alternatively, the portfolio model could be applied to just those origin countries-nationalities with the same level of public health risk as the destination country, allowing "travel corridors" or "travel bubbles" (Sharun et al., 2021) between origin and destination countries. This model would generate the optimal tourist mix when there is easy (quarantine-free) access to tourists from countries with a similar public health risk. These two adaptations of the portfolio model (an additional public health risk goal, and considering only similar public health risk origin countries) could be the subject of future research.

Both business commentators and tourism experts suggest that tourism will rebound (Economist, 2021), and once the travel fear is overcome (Dedeoğlu, Mariani, Shi, & Okumus, 2022;Zheng et al., 2021), the extent to which people travel may even increase. As COVID-19 subsides, the benefits of diversification across tourist markets will return, and updated correlations and expenditure per bed night can be used in future tourism portfolio modelling research.

Last, while most of the tourism portfolio literature focuses on the country of origin of tourists, we know that today marketing and digital marketing research is increasingly using a number of variables including online behavioural and psychographic variables such as website users' search patterns (Dias & Vermunt, 2007) or online reviewers' behaviours and experience (Dolnicar, 2021; Mariani & Borghi, 2021). That said, there is still a theory-practice divide in marketing segmentation (Dolnicar & Lazarevski, 2009), and in practice destination marketers and DMOs still heavily rely on easy to measure variables (Mariani, 2020) such as the country of origin (Morrison, 2019) and the geographic distance (Henok, 2021; McKercher et al., 2008) as two-thirds of all international travel occurs to places within 2000 km of a source market

(McKercher & Mak, 2019). To a certain extent, and with some limitations (such as the use of proxy servers), the geographical source of web traffic can be considered as a suitable proxy for more traditional segmentation variables like the country of origin and geographical distance. Accordingly, future tourism portfolio research might try to juxtapose the traditional segmentation variables of country of origin and geographical distance to other variables (such as the geographical source of web traffic stemming from travel searches) whose measurement is easy for digital marketers working for DMOs or to market destinations.

Funding information

No funding was received for this research/paper.

Credit author statement

Marcello Mariani: Conceptualization, Writing – original draft, Writing – review & editing, Emmanouil Platanakis: Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Dimitrios Stafylas: Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Charles Sutcliffe: Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review & editing,

Impact statement

This research contributes applied knowledge to the tourism industry and the wider society. As tourism destination managers and marketers of national DMOs want to improve the performance and competitiveness of their destinations, they should make a careful decision when choosing the tourism portfolio models they use to determine the optimal mixture of tourist markets. We argue that they should use the Levels Model 1, and not the Growth Rates model or the Levels Model 2. The Levels Model 1 generates implementable solutions which will result in improved destination performance. Tourist destination managers/marketers and policy makers who choose not to target an optimal tourist market mix, or who do so using a flawed model, could potentially sacrifice both tourist income and a reduction in its variability.

Declaration of competing interest

None.

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