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Comovement amongst the demand for New Zealand tourism

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ABSTRACT

Tourism research is replete with applications of univariate time-series decomposition techniques: multivariate frameworks have been largely ignored. In this paper, we employ a common-feature-based, multivariate trend-cycle decomposition approach to examine common trends and common cycles amongst the demand for New Zealand tourism originating in Australia, China, the US, the UK, as well as other tourism-importing countries considered as one group: Others. Upon isolating trends and cycles in tourism demand from these countries, we find evidence of strong long-term comovement: they share one common trend. We also find evidence of short-term comovement, albeit to a lesser extent: four common cycles emerge; the cyclical patterns in tourism demand from Australia, China, the US, and Others are strongly correlated.

Introduction

Trends (i.e., long-term patterns), cycles (i.e., short-term patterns), and seasonality characterize tourism demand. However, they are not directly observable. Thus, researchers have employed various decomposition techniques to isolate the sub-components of the observed, aggregated time-series to examine the short- and long-term patterns of tourism demand. While univariate and bivariate decomposition frameworks predominate the tourism literature (Chan & Lim, 2011; Coshall, 2000a; Coshall, 2000b; Hassani, Webster, Silva, & Heravi, 2015; Li & Law, 2019; Ridderstaat & Croes, 2017; Wu & Wu, 2019; Zhang et al., 2017), multivariate decomposition has been largely ignored thus far: this is a gap in the literature. In this paper, we bridge this gap by employing a multivariate trend-cycle decomposition framework to illuminate common trends (i.e., long-term comovement) and common cycles (i.e., short-term comovement) in the international demand for New Zealand tourism. Thus, we further the scope of econometric modeling in tourism research.

A brief background is in order to contextualize the analysis. In 2018, the tourism industry contributed $39 billion to New Zealand's economy; this was 20% of its GDP. In the same year, international tourism, which is the largest export industry of New Zealand, accounted for 21% of its foreign exchange earnings and generated $16 billion in revenue (Statistics New Zealand, 2019a). Furthermore, Australia, China, the United States (US), and the United Kingdom (UK), accounted for 63% of international visitor arrivals (VAs): see Table 1. Evidently, the tourism demand originating in these countries is pivotal to the success of the tourism industry of New Zealand; and the success of the tourism industry is critical to New Zealand's economy. To be sure, travelers from a multitude of other countries visit New Zealand; however, when considered country-by-country, each accounts for < 5% of the aggregate VAs to New Zealand, with the three most significant of the other countries–Germany, Japan, and South Korea–contributing 4%, 3%, and 3% of the total VAs to New Zealand, respectively. Of course, when the other countries are grouped, they account for more than one-third of the total VAs to New Zealand: thus, their inclusion, albeit in the form of a group of countries, is warranted.

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Table 1
VAs for holiday and vacation to New Zealand in 2018.

	AU	CH	US	UK	OT
Number of VAs	591,617	341,721	235,513	104,721	747,997
% of total	29%	17%	12%	5%	37%
Monthly average	49,301	28,477	19,626	8689	62,333
Annual growth[a]	3%	14%	5%	12%	9%
Coefficient of variation~	27	42	62	70	47

[a] Calculated as the mean of the annual growth rates between 2013 and 2018;~ calculated for the entire sample period.

Accordingly, in this paper, we investigate the commonalities in the short- and long-run between inbound tourism to New Zealand from Australia, China, the US, the UK, as well the remaining countries, which we group under one category: Others.

Tourism demand is impacted to varying degrees by a multitude of factors, many of which tend to be country-specific. Examples of these factors include marketing initiatives, whose designs, implementations, and outcomes may vary across tourism-importing countries; also, due to immigration policies, national security interests, as well as health and safety concerns, differences in visa regulations across countries are to be expected: restricting the entry of travelers coming to New Zealand from mainland China on February 3, 2020, to protect the nation from the effects of Covid-19 is a case in point; these restrictions were imposed on travelers from other countries as well, albeit with a lag. Other factors–such as changes in oil prices (Becken, 2008; Becken, 2010; Becken & Lennox, 2012; Chatziantoniou, Filis, Eeckels, & Apostolakis, 2013; Dhaoui, Sekrafi, & Ghandri, 2017), hosting sporting events and pandemics (Sun, Rodriguez, Wu, & Chuang, 2013), terrorist activities (Adams, Dixon, & Rimmer, 2001; Raza & Jawaid, 2013; Thompson, 2011), and natural disasters (Murakami, Kawamura, & Suzuki, 2012; Sun et al., 2013)–may be correlated across countries. However, these factors may elicit varied responses from tourists in different countries, and cause the trajectories of tourism demand to diverge. Conversely, broad access to information, global interconnectedness (Cao, Li, & Song, 2017), relative prices (Dogru, Sirakaya-Turk, & Crouch, 2017; Schiff & Becken, 2011; Song, Li, Witt, & Fei, 2010) and rising incomes (Bhattacharya & Narayan, 2005) may engender comovement amongst tourism demand originating in different countries.

Of the many factors mentioned above, it is repeatedly found and widely accepted that incomes–which are generally represented by the real GDPs–and relative prices exert significant influence on tourism demand in different countries; while other factors may be relatively unimportant, they too can have, at the very least, small and short-lived impacts. In any case, due to the effects of, and the interplay between a myriad of factors (including, but not limited to the ones mentioned above), and due to a high degree of global interconnectedness, tourism demand originating in different countries can exhibit common trends and cycles that manifest themselves in the form of synchronous fluctuations in tourism demand across countries. Indeed, understanding the commonalities in the behavior of tourism demand at different horizons provides valuable information to policymakers and industry stakeholders.

Accordingly, it is important to examine the tendency, or the lack thereof, of trends and cycles in international tourism demand to synchronize, especially given that some of the potential determinants of tourism demand–such as national incomes, economic policy, money supply, international sporting events, and visa policies–are beyond the influence of many stakeholders in the tourism industry. Noting that there is an abundance of research on the determinants of tourism demand (for example, Schiff and Becken (2011) have examined price and income elasticities in the context of New Zealand tourism; Tsui, Balli, Tan, Lau, and Hasan (2018) have examined the role of economic policy uncertainty on New Zealand's business tourism using a gravity model), we want to make a meaningful contribution to tourism research by focusing on the subject of comovement. Unlike previous analyses, we use a common-features-based multivariate framework to isolate and examine trends and cycles amongst international tourism demand. In doing so, we present a complementary perspective that can be used in conjunction with the extant literature to build a more comprehensive framework for tourism analysis.

Univariate decomposition frameworks are used extensively in tourism research to isolate trends and cycles in different variables. Once isolated, these sub-components from different variables are co-examined in more detail to study their long- and short-term relationships. However, because each variable is decomposed separately, this approach can overlook their tendencies to respond similarly, both in the short- and long-run, to changes in the business, economic, social, and political environments. This has important implications, as these similarities can cause the variables to move together. For example, while one may isolate the cycles–in say, tourism demand, money supply, and output, with the aid of Hodrick-Prescott (HP) filter (Croes, Ridderstaat, & Rivera, 2018; Ridderstaat & Croes, 2017; Smeral, 2012)–and subsequently use them in regression frameworks, such an approach would not reveal the presence of common features, a form of co-dependence amongst the variables (Engle & Kozicki, 1993; Vahid & Engle, 1993). These co-dependencies, when they exist, indicate that the variables co-move in the short-run, i.e., they have similar cyclical components. This highlights the importance of joint-treatment of the variables, as it leverages information on each of them simultaneously. Moreover, analyses of cycles derived from univariate decomposition techniques do not address the presence of common trends amongst the variables. Given the high degree of interconnectedness in global tourism demand (Assaf, Li, Song, & Tsionas, 2019), disregarding common trends–the presence of which is distinctly possible–would yield incomplete information about comovement, which may lead to incorrect conclusions.

When using univariate smoothing techniques, which are ubiquitous in tourism research, one often grapples with ad hoc choices. The HP filter illustrates this point well as its application requires one to choose a suitable value for a smoothing parameter to isolate trends and cycles. This value determines the trade-off between the smoothness of the trend on the one hand, and how well the trend fits the data on the other. Moreover, different smoothing-parameter values can yield significantly different results. While some values are more commonly used than others, they are all ad hoc nonetheless. The latitude afforded by such ad hoc techniques often generates spurious results. Furthermore, when trends and cycles obtained from several individually treated data series are juxtaposed to estimate interrelationships between them within regression frameworks, researchers contend with balancing the simplicity of the models on the hand, and their predictive power on the other.

In this study, we overcome the aforementioned limitations associated with univariate decomposition techniques. We present a novel perspective on the synchronization amongst the demand for New Zealand tourism originating in different countries within the framework developed by Vahid and Engle (1993). The use of this multivariate decomposition framework lends itself well to such analyses: it obviates the need to estimate separate models to isolate trends and cycles amongst the time-series in question; it reduces the complexity of multivariate models, as variables that move together may have common components, the presence of which simplifies the econometric models while maintaining their predictive power; it addresses the commonalities amongst the cyclical components in conjunction with commonalities amongst the long-term trends; and it enables us to examine the dynamic relationship amongst the variables in light of their responsiveness to the ever-changing socio-economic and business environments.

It is noted that multivariate methods–such as cointegration and vector error correction (VEC) models (Halicioglu, 2010; Lim & McAleer, 2001; Song, Lin, Witt, & Zhang, 2011) and vector autoregression (VAR) models (Cao et al., 2017)–have been used in tourism literature. However, none of these papers has sought to isolate trends and cycles in tourism demand. Although cointegration is a useful approach to study long-term trends and comovement amongst variables, short-term comovement is of interest to various stakeholders in the tourism industry. After all, many policies are designed, and business decisions are made, with the short-term in mind. Also, the understanding of cyclical behavior can be used to generate short- to medium-term forecasts (Coshall, 2000b). Nonetheless, short-term dynamics have not received due attention.

Accordingly, using a decomposition-centric analysis, we extend the application of multivariate modeling frameworks in tourism research: as such, we study long-term (or non-stationary) as well as short-term (or stationary) forms of persistence and comovement. In essence, we coalesce–and in doing so, bridge a gap between–two strands of literature, one that is predicated on the decomposition of time-series (but in univariate and bivariate frameworks), and the other that leverages multivariate frameworks (but does not involve time-series decomposition).

The results of our analysis will be of interest to various stakeholders in the tourism industry: accommodation providers, transportation companies, marketers, amongst others. A deeper understanding of the synchrony between VAs from major tourism-importing countries would assist in the optimization of revenue management, pricing strategies, hiring decisions, marketing initiatives, and financial forecasting; the simplicity of a reductionist perspective, predicated on the tendency of tourism demand from different countries to synchronize, offers intelligible and thus, actionable insights.

Next, we discuss some practical applications to ground the econometric concepts and techniques employed in this study. Conceptually, the analysis of comovement amongst tourism demand is akin to that of comovement amongst the oft-studied economic and financial time-series such as the real GDP, stock markets, exchange rates, and energy prices. Such time-series tend to meander unpredictably. However, if common trends amongst the series that remain stable over time can be identified, information about one series can be gleaned from the behavior of other series with which the former shares common trends; furthermore, information on such commonalities can be incorporated in forecast-models (Harvey, 1997).

Let's consider this in context of tourism demand more closely. Industry stakeholders, such as accommodation providers or firms that design tourism packages, are often interested in learning about the nationalities and corresponding profiles of inbound tourists in order to optimize their products and services. In such cases, the extent to which VAs from a set of nations tend to follow similar patterns equips the stakeholders with useful information for devising tourism initiatives that appeal to the customers from those nations. Furthermore, if stakeholders, based on their knowledge of comovement amongst VAs, expect that a decline in tourism demand from one nation is likely to coincide with that from other nations that share common trends, the stakeholders may diversify their product and service offerings to cater to a wider or alternate customer base which may be based in either the domestic or other international markets that exhibit different trends.

The alpine ski industry provides an example. Over the past two decades, as the cost of alpine skiing has been increasing faster than increases in average compensation levels in most countries, annual skier visits–and especially international skier visits–to ski resorts have been declining. Many ski resorts have responded by expanding their service offerings to provide lift-accessed mountain biking experiences, which has grown in market size within the domestic markets where the resorts are situated. Due to the restrictions on international travel, such practices will become common in the aftermath of the Covid-19 pandemic.

Other risk mitigation strategies may also be devised: resources that are allocated to tourism services may be re-purposed to other business initiatives, for example, tourist coaches and buses may be leased to the city or to schools, and accommodation infrastructure may be rented to students or used as convention centers.

Importantly, to understand the nature and degree of comovement amongst VAs in this modeling framework, no a priori assumptions about the underlying data-generating processes are necessary. Additionally, considering the absence of other variables such as the real GDP, terrorist activities, epidemics, and money supply, amongst others, stakeholders do not have to calibrate their understanding of inbound tourism based on the impacts of each of the several simultaneously changing variables. The comovement-centric perspective provides practicable insights in a tractable and straightforward fashion.

Also, given the importance of international tourism to New Zealand's economy, the results of this analysis regarding the synchronization amongst the number of VAs may inform policies associated with the following: infrastructure development–a large influx of visitors may overwhelm small resort towns such as Queenstown, New Zealand, whose infrastructure often proves to be inadequate; unemployment assistance programs–14% of the New Zealand workforce is employed by the tourism sector (Stats NZ TSA, 2019); taxation–both income taxes, considering the employment statistics presented in the previous point, as well as tourist-taxes to raise revenues from visitors (Hostelworld, 2019). Last but not least, in light of the relationship between tourism demand, prices, and currency exchange rates (Agiomirgianakis, Serenis, & Tsounis, 2014; Akay, Cifter, & Teke, 2017; Crouch, 1993; Crouch, 1995; Kuncoro, 2016; Webber, 2001), a deeper understanding of tourism dynamics–by putting tourism in the frame of reference–may aid the development of monetary policy.

Tourism demand and time-series decomposition

Research on identifying the *determinants* of tourism demand has received considerable attention. Amongst them, income of the tourists, prices in the tourists' home countries, and prices in various destination countries have emerged as the key drivers (Quayson & Var, 1982; Song, Witt, and Li, 2009; Schiff & Becken, 2011; Dogru et al., 2017; Kim and Lee, 2017; Pham, Nghiem, and Dwyer, 2017; Mohammed, 2019).

Given the importance of income to tourism demand, it is unsurprising that the latter has been investigated in light of business cycles. Various time-series techniques have been leveraged to conduct these analyses: Guizzardi and Mazzocchi (2010) used latent-cycle-component, and economic-explanatory-variables models to study stochastic trends and stochastic seasonality in tourism demand in Italy; Croes and Ridderstaat (2017) and Croes et al. (2018) employed the HP filter (to extract the cyclical components), the Engle-Granger cointegration method, causality tests, and 2-Stage-Least-Squares framework to investigate the association between business cycles and tourism demand in Aruba and Barbados. Such analyses seek to understand tourism demand by regressing it on various explanatory variables. In doing so, the relative importance of different factors is identified. Our approach is similar to the one used in Narayan (2011), who studied business cycles and tourism expenditure in Australia using the common-trend and common-cycle framework developed by Vahid and Engle (1993). While Narayan (2011) examined the relative importance of transitory and permanent shocks to the dynamics of tourism expenditure in, and the real GDP of Australia, we illuminate the nature and degree of short- and long-term comovement between the number of VAs to New Zealand from major tourism-importing countries by identifying and isolating the trend and cyclical components of the VAs series.

Spectral techniques (Chan & Lim, 2011; Coshall, 2000a, 2000b; Eeckels, Filis, & Leon, 2012; Lyu, Yang, Na, & Law, 2016), which yield sine and cosine functional representations of the sub-components of time-series, have also been used widely to study trends and patterns in tourism demand: cyclicality and seasonality–two of its characteristic features–have received considerable attention. However, often, a distinction between the two is not drawn–seasonality itself is classified as a cyclical feature. Note that seasonality exerts a significant influence on tourism demand, and can account for a large proportion of its total variance. This was evident in the results reported by Coshall (2000a), who employed univariate and bivariate spectral analysis to examine commonalities in cyclical variations in seasonally-unadjusted passenger flows from the UK to a subset of OECD countries, and currency exchange rates vis-à-vis the Sterling: the cyclical patterns that emerged reflected strong seasonal variations. Coshall (2000b) used the same approach to examine cycles in tourists' expenditures in the UK: periodicities in tourism expenditure were examined with the aid of univariate analysis, whereas, the bivariate spectral framework was employed to investigate cyclical dependencies between tourism expenditure and exchange rates.

Spectral analysis was applied in the context of New Zealand by Chan and Lim (2011). Upon examining the seasonal patterns in inbound tourism to New Zealand originating in Australia and the US, they reported that the number of VAs in separate travel categories–Holiday and Vacation, Visiting Friends and Relatives, and Private and Official Business–share similar cycles. To be clear, Chan and Lim (2011) emphasized commonalities in intra-country seasonal patterns across different visitor categories within a univariate framework. In contrast, we analyze inter-country trends and cycles amongst VAs in a multivariate framework. Hassani et al. (2015) utilized *univariate* vector singular spectral analysis (VSSA) to generate forecasts of tourist arrivals to the US. In the VSSA framework, the noise is extracted from the original series via decomposition, and in turn, new (less noisy) series is constructed. The latter is then used for forecasting purposes. Hassani et al. (2015) showed that VSSA-based forecasts outperformed the ones generated from ARIMA, exponential smoothing, and neural network methods.

Considering the non-stationary nature of tourism demand data, the application of spectral analysis has limitations. Thus, data are subject to differencing and logarithmic transformations in order to enforce stationarity (Coshall, 2000a, and 2000b; Chan & Lim, 2011). It is well-recognized that, to examine the associations amongst non-stationary data, performing regression analysis on their differenced forms is unsuitable, as it leads to information-loss about the long-term dynamics. However, wavelet decomposition analysis lends itself well to the analysis of non-stationary data. With the aid of this framework, Sharif, Saha, and Nanthakumar (2017), and Wu and Wu (2019) examined the associations of tourism demand with economic growth and European policy uncertainty, respectively.

More recently, Zhang et al. (2017) employed the Ensemble Empirical Mode Decomposition (EEMD) method in conjunction with the well-known ARIMA framework to forecast hotel occupancy rates. They reported that the integrated EEMD-ARIMA method enhanced short-term forecasts. Li and Law (2019) also applied EEMD to decompose (Google Trends) search engine data, derive cyclical components, and build forecasts of tourist arrivals to Hong Kong from nine countries.

The popularity of smoothing techniques (Andrew, Cranage, & Lee, 1990; Coshall, 2009; Hassani et al., 2015) is unmistakable in the time-series tourism literature: their prevalence is noted by Song, Qiu, and Park (2019). Several authors have used these techniques to extract cyclical components from the observed data, and in turn, regress them on different variables of interest. The HP filter–in combination with other techniques–has been used widely to this end (Cao, Huang, Jin, & Xu, 2016; Gouveia & Rodrigues, 2005; Kuncoro, 2016; Ridderstaat & Croes, 2017). For instance, Cao et al. (2016) measured tourism efficiency in China by employing HP filters (to isolate economic fluctuations) in conjunction with empirical mode decomposition (EMD) and wavelet decomposition: economic fluctuations were then regressed on various efficiency-variables to evaluate tourism efficiency. Croes and Ridderstaat

(2017) applied the cointegration, VEC, and Granger-causality methods to study the association between money demand and tourism demand cycles: they extracted the cyclical components using the HP filter. The techniques mentioned above entail choices regarding the appropriate damping factors and multipliers. In turn, these choices–which are fraught with arbitrariness–along with other methodological characteristics, influence the nature of the resultant cyclical patterns.

Given the HP filter's pervasiveness in time-series research, it is befitting to use it as an exemplar. Economic time-series tend to follow random walks. The first-differences–i.e., the change occurring from one period to the next–of a random walk process should get rid of its predictable component. The HP filter, however, applies several levels of differencing. Hamilton (2018) notes that such treatment gives rise to cyclical patterns that are devoid of any association with the underlying data-generating process. Rather, they are artifacts of the HP filter itself. Moreover, even when applied in the context of multivariate models, the cycles are isolated from each variable individually: the technique is, after all, univariate, and does not leverage information on all the variables jointly. Consequently, such models yield spurious results, especially considering that the cycles yielded by the HP filter may be themselves be spurious. Accordingly, using the HP filter to study economic data, particularly within multivariate models, is sub-optimal.

Our approach deviates from the application of univariate and bivariate techniques that have been employed repeatedly in the literature. We employ a common-features-based, multivariate trend-cycle decomposition framework, which utilizes the information on the short-term as well as the long-term interlinkages amongst the five time-series simultaneously, in order to isolate their cyclical and trend components. In turn, these clearly delineated components are used to analyze short- and long-term comovements amongst the said variables.

Data

We use monthly data from Jan 2013 to January 2020 on the number of VAs for the purpose of holiday or vacation from Australia, China, the US, the UK, and Others. VAs are defined as overseas residents arriving in New Zealand for a stay of fewer than 12 months. The data are obtained from the Statistics New Zealand Infoshare website (Stats NZ Infoshare, 2019b).

A simple visual inspection of the data makes a good starting point. The original time-series are plotted in Fig. 1, from which some fundamental trends and patterns are readily observed: expectedly, there are seasonal variations in the number of VAs–in general, peaks are observed during the summer months of December, January, and February, whereas troughs are observed during the winter period from June to August; while VAs from Australia decline sharply during April and May, those from China tend to be the lowest during June and July, and those from the US bottom out during August and September. The data in Table 1 show that the number of VAs from China has registered the highest growth rate since 2013, closely followed by that from the UK; however, the latter is significantly more volatile. Notably, the number of VAs from Australia has increased only modestly in comparison to those from the other countries and is also the least volatile. The number of VAs from the category Others is in the middle of the spectrum in terms of both growth rate and volatility.

Prominent seasonal patterns, notwithstanding the differences amongst them across tourism-importing countries, may invoke a perception of comovement amongst international tourism demand in different countries. More importantly, seasonality may veil the underlying trends and cycles, the analysis of which is the focus of this paper. Hence, we apply the ARIMA-based U.S. Census Bureau's X-12 seasonal adjustment method to address the issue of seasonality before proceeding with the analysis. We also use other moving-average based adjustment techniques to verify the robustness of the X-12 method: they generate similar results. The plateauing of VAs from 2016 to 2018, following a sustained upward trend, is manifest in the seasonally adjusted data plotted in Fig. 2. While this pattern is most conspicuous in the case of Chinese visitors and those from Others, it is visible in the number of VAs from Australia and the US as well. More recently, however, VAs to New Zealand (particularly from China and Others) have declined. On the whole, commonalities of varying degrees amongst the trajectories of tourism demand originating in different countries are evident. While visual inspection of the data is informative, it is important to derive cycles and trends from the observed data using formal econometrics to gain deeper insights into the short- and long-term patterns of tourism demand. However, before deriving them, it is natural to ask, which factors shape trends and cycles?

The channels through (and the extent to) which various factors influence tourism demand vary. Changes in some factors such as sustained increases in the number of flights to and from different countries, abiding relaxation of visa regulations, and word-of-

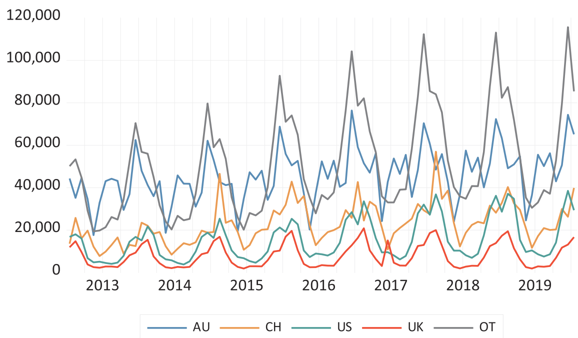

Fig. 1. Original series: monthly VAs.

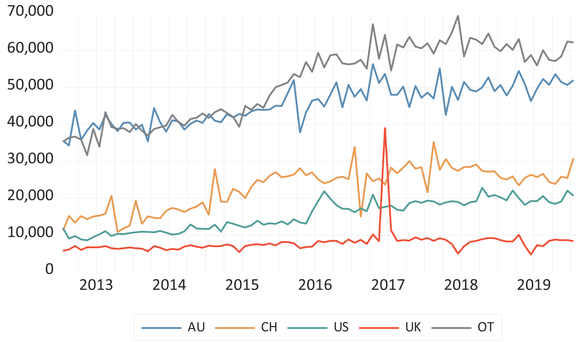

Fig. 2. Seasonally adjusted series: monthly VAs.

mouth, may exert a persistent influence on tourism demand, and thereby alter its long-term trend. On the other hand, sensitivity to marketing initiatives and discount pricing may engender transitory changes in tourism demand, which would manifest themselves in the form of short-term cycles. Nevertheless, some factors influence both cycles and trends in tourism demand.

In this study, we select the method developed by Vahid and Engle (1993), as it allows us to test for the presence of common cycles amongst variables that share common trends, as well as to isolate cycles and trends in tourism demand in a unified framework: thus, it duly addresses our principal objectives. In the next section, we discuss the method in more detail.

Methodological framework

A series is said to be integrated of order d, i.e., $I(d)$, if its *d'th* difference is stationary. Now, consider a group of $I(1)$ variables that drift along their respective trends. If, however, there is a linear combination of these variables that is $I(0)$, then the rate at which these variables drift would be approximately the same. They shall remain anchored to the long-term equilibrium between them, and any deviations from the equilibrium would be transient. Thus, the short-term behaviors of these variables would be dictated by the extent to which they deviate from the long-term equilibrium. Such variables are said to be cointegrated, and they share common stochastic trends. According to (Johansen, 1988), if $x_t$is an $(n \times 1)$ vector of $I(1)$ variables, then there can exist $r < n$ linearly independent cointegrating vectors. The $(n \times r)$ matrix β consists of the linearly dependent cointegrating vectors, and $\beta' x_t$ is $I(0)$. The range of β is the cointegrating space.

The trend-cycle decomposition method proposed by Vahid and Engle (1993) is predicated on the presence of cointegration amongst a set of $I(1)$ variables. They coalesced the idea of cointegration with the serial correlation common features testing framework developed by Engle and Kozicki (1993). The latter seeks to detect features in time-series, and common features amongst them, by testing for the presence of a non-zero linear combination that is devoid of the feature.

Cointegration implies the presence of long-term equilibria. Nevertheless, economic forces continually buffet cointegrated variables, thereby causing them to deviate intermittently from the long-term equilibria. These transitory deviations are called cycles. Hence, $I(1)$ series may be decomposed into two additive components: trend and cyclical. Vahid and Engle (1993) demonstrated that, in the presence of common features amongst the first-differenced forms of a set of cointegrated $I(1)$ variables, common cycles may be obtained upon the removal of common trends from the level forms of the series. They showed that "with r linearly independent cointegrating vectors, if x_t has common cycles, there can, at most, exist $(n - r)$ linearly independent cofeature vectors that eliminate common cycles" (Vahid & Engle, 1993, pp. 345, Theorem 1). Thus, the existence of $r < n$ linearly independent cointegrating vectors entails the presence of at most $s = (n - r)$ linearly independent cofeature vectors and $(n - s)$ common cycles; s and r are also linearly independent; the range of the $(n \times s)$ matrix is called the cofeature space, $\widetilde{\beta}$. The number of common cycles can be determined by testing for the significance of the canonical correlations amongst Δx_t *and* $(\beta' x_{t-1}, \Delta x_{t-1}, \Delta x_{t-2}, \ldots, \Delta x_{t-p+1})$ where p is the chosen lag-length of the Vector Autoregression (VAR) model.

In this paper, we leverage a special case in which the sum of the number of common trends, and the number of common cycles, is equal to the number of variables. In the jargon of this paper, $r + s = n$. This renders the $(n \times n)$ matrix $B = \begin{bmatrix} \widetilde{\beta}' \\ \beta' \end{bmatrix}$ of full-rank. Thus, B^{-1} exists. Upon partitioning B^{-1}, such that $B^{-1} = [\widetilde{\beta}^{-} \mid \beta^{-}]$,the trend and cyclical components can be recovered as follows:

$$x_t = B^{-1} B x_t = \widetilde{\beta}^{-} \widetilde{\beta}' x_t + \beta^{-} \beta' x_t = Trend + Cycle. \tag{1}$$

$\widetilde{\beta}' x_t$ does not contain any cycles; it is a random walk. Therefore, $\widetilde{\beta}^{-} \widetilde{\beta}' x_t$ represents the trend component. On the other hand, $\beta' x_t$ is stationary and serially correlated. Thus, $\beta^{-} \beta' x_t$ represents the cyclical component.

The serial-correlation-common-features (Engle & Kozicki, 1993), and the common-trends-and-common-cycles (Vahid & Engle, 1993) frameworks have been used in various contexts to study comovements amongst a multitude of economic and financial time-series. For a detailed review of the application of these frameworks, please see the following: Engle and Kozicki (1993); Vahid and Engle (1993); Witt, A. Clarke, and Fielding (1998); Morley and Pentecost (2000); Cheung and Westermann (2002); Wongbangpo and Sharma (2002); Serletis and Rangel-Ruiz (2004); Shirvani and Wilbratte (2007); Lindenberg and Westermann (2009); Narayan and

Table 2
Unit root tests.

Test	AU	CH	US	UK	OT
$t_{\alpha\text{-}}$	1.36	0.99	0.80	−1.06	1.47
$t_{\alpha\sim}$	−1.25	−1.56	−1.47	−7.57[a]	−1.17
z-$t_{\alpha\text{-}}$	−0.75	0.54	0.62	−1.84	1.28
z-$t_{\alpha\sim}$	−3.79[a]	−3.46[a]	−1.10	−7.65[a]	−1.44
KPSS	1.26[a]	1.04[a]	1.11[a]	0.47[a]	1.06[a]

The null hypothesis for the tα- and tα∼ ADF tests (Dickey & Fuller, 1979, 1981), and for the z-tα- and z-tα∼ Phillips-Perron (Phillips & Perron, 1988) tests is that the series is non-stationary. For the KPSS test (Kwiatkowski, Phillips, Schmidt, & Shin, 1992), the null hypothesis is that the series is stationary. The lag-length for the ADF tests is chosen by minimizing the AIC criteria.

The lag-length for the Phillips-Perron tests is determined by using the Schwert (1989) formula: $Int\left\{4\left(\left(\frac{T}{100}\right)^{0.25}\right)\right\}$.

[a] Indicates the rejection of the null hypothesis at 5% significance level.

Thuraisamy (2013); Basnet, Vatsa, and Sharma (2014); Basnet, Sharma, and Vatsa (2015); and Balcilar, Gupta, and Wohar (2017).

Empirical evidence

We conduct several unit root tests to ascertain the stationarity properties of the five time-series. The majority of the tests indicate that the series are non-stationary. The results of the unit root tests are presented in Table 2. Next, following (Sims, 1980), we determine the optimum lag-length of the VEC model by conducting sequential likelihood ratio (LR) tests on the unrestricted VAR model comprising the level forms of the five time-series. Accordingly, beginning at lag eight and decreasing the number of lags one at a time, we compute the LR statistics and compare them to the corresponding 5% critical values. This process is terminated upon the rejection of the first null hypothesis–we select the lag-length consistent with the alternative hypothesis. This process yields an optimum lag-length of four lags. A VAR of order four entails a VEC model of order three. We adhere to this lag-length throughout the remainder of the analysis.

Thereafter, we employ the maximum-likelihood based, Johansen (1988) cointegration methodology to test for the presence of long-term comovement (or common trends) amongst the five time-series. We consider two specifications of the VEC model, one under the null hypothesis, and the other under the alternative, i.e.,

$$H_0\colon \Delta x_t = \alpha(\beta' x_{t-1} + \delta_0) + \sum_{i=1}^{p-1} \omega_i \Delta x_{t-i} + \epsilon_t \tag{2}$$

$$H_A\colon \Delta x_t = \alpha(\beta' x_{t-1} + \delta_0) + \tau\gamma_0 + \sum_{i=1}^{p-1} \omega_i \Delta x_{t-i} + \epsilon_t \tag{3}$$

where $x_t = (AU_t, CH_t, US_t, UK_t, OT_t)'$ is a (5×1) vector, and AU_t, CH_t, US_t, UK_t, $and\ OT_t$ represent the number of monthly VAs from Australia, China, the US, the UK, and Others respectively; α is the vector of adjustment coefficients; $\tau\gamma_0$ represents the deterministic terms outside the cointegrating relations; $\omega_i$represents the $(n \times n)$ coefficient matrices; and ϵ_t is the vector of innovations. Considering that the proportion of the drift that is included in the cointegrating relation is arbitrary, an identification strategy is needed. As such, it is identified in a manner that forces the error-correction term to have a sample-mean of zero. Using the LR test, we fail to reject the null hypothesis at 5% significance: the computed LR statistic 7.52 is smaller than the ${\chi_{(4)}}^2$ critical value of 9.49. Thus, we select the error correction representation consistent with the null hypothesis.

Both the λ_{trace} and the λ_{max} statistics reveal the presence of four cointegrating relations at the 10% significance level. However, at the 5% significance level, the two yield different results: on the one hand, the results associated with the λ_{trace} statistics remain unchanged, whereas on the other, the λ_{max} statistics indicate the presence of two cointegrating relationships. Given that the λ_{trace} statistics test the null hypothesis that the number of distinct cointegrating vectors is less than or equal to r, they tend to have greater power relative to the λ_{max} statistics (Kasa, 1992; Serletis & King, 1997). Accordingly, we allow the results associated with λ_{trace} statistics to take precedence and conclude that $r = 4$. In other words, the five time-series share one common trend. The results of the

Table 3
Cointegration tests.

Null hypothesis	Eigenvalue	Trace	Max
$r = 0$	0.40	116.59**	41.88**
$r \le 2$	0.33	74.71**	32.10**
$r \le 3$	0.23	42.61**	21.26*
$r \le 4$	0.18	21.35**	15.61*
$r \le 5$	0.07	5.74	5.74

*(**)indicates the rejection of the null hypothesis at 10%(5%)significance level.

Table 4
Tests for common cycles.

Null hypothesis	ρ_i^2	$C(p,s)$ d. f	$C(p,s)$
s > 0	0.25	15	24.17
s > 1	0.80	32	161.54[a]
s > 3	0.93	51	388.53[a]
s > 4	0.95	72	637.72[a]

[a] Indicates the rejection of the null hypothesis at 5% significance level; C(p,s) is calculated in accordance with the test statistic proposed by Vahid and Engle (1993).

cointegration tests are presented in Table 3. The Lagrange multiplier autocorrelation test indicates no serial correlation amongst the residuals.

The test for common cycles is conditional upon the presence of common stochastic trends. Therefore, following Vahid and Engle (1993), we determine the number of significant canonical correlations, which yield the number of common cycles, as well as the dimensions of the cofeature space. Hence, we utilize the test statistic proposed by Vahid and Engle (1993), which is expressed as follows:

$$C(p,s) = -(T-p-1)\sum_{i=1}^{s} ln(1-\rho_i^2) \tag{4}$$

where T is the number of observations, p is one less than the chosen lag-length of the unrestricted VAR model, and ρ_i^2 are the squared canonical correlations. $C(p,s)$ has a χ^2 distribution with $s^2 + snp + sr - sn$ degrees of freedom. Using this test, the results of which are reported in Table 4, we detect only one non-zero canonical correlation; this implies the presence of one cofeature vector. In other words, there are four common cycles, i.e., $n - s = 5 - 1 = 4$. Thus, the matrix comprising the cointegrating and cofeature vectors is of full-rank: $r + s = 4 + 1 = 5 = n$. Hence, we can invert the matrix as described in section 4, and in turn, decompose the original series into their trend and cyclical components.

The trend components plotted in Fig. 3 are proportional to (and perfectly correlated with) one another. Considering the presence of one common trend, this is to be expected. This result indicates strong long-term comovement amongst the number of VAs to New Zealand from the four primary tourism-importing countries, as well as the group Others. That is to say, in the long-term, the demand for New Zealand tourism originating in various countries will remain tethered to a stable equilibrium–while tourism demand from individual countries may deviate intermittently from the long-term relationship, the error-correction mechanism implied by the presence of cointegration will ensure that these deviations are short-lived. This result stands to reason, especially when viewed in the context of a deeply connected global economy and secularly rising national incomes, both of which combine to give rise to a common global growth factor: it is conceivable that the latter is indeed the force –manifested in the common trend–that is driving the long-term dynamics of tourism demand in different countries, causing them to exhibit proportionality. Thus, in the future, as the world progresses towards greater interconnectedness, and national incomes continue to rise, one can expect the demand for New Zealand tourism in different countries to exhibit similar upward trends over the long-term. Nevertheless, tourism demand in different countries may exhibit different behaviors in the short-term. In order to examine these in greater detail, we turn our attention to the cyclical components. These are illustrated in Fig. 4.

Considering that there are four common cycles compared to one common trend, it is unsurprising that unlike the trend components, the cyclical components are not proportional. Nevertheless, they are very similar to one another. This is especially true for Australia, China, the US, and Others. The cyclical component in the case of the UK, on the other hand, is not as strongly correlated with those of the other four series.

The correlations between the cyclical components, which are reported above the main diagonal in Table 5, confirm these observations. Amongst different bivariate combinations, excluding those that comprise the UK, the correlations are > 0.92; most

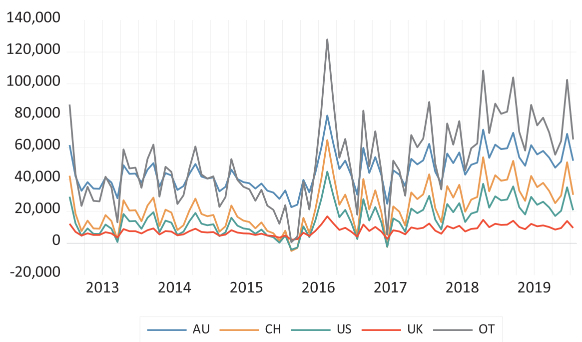

Fig. 3. Trend components: long-term co-movement.

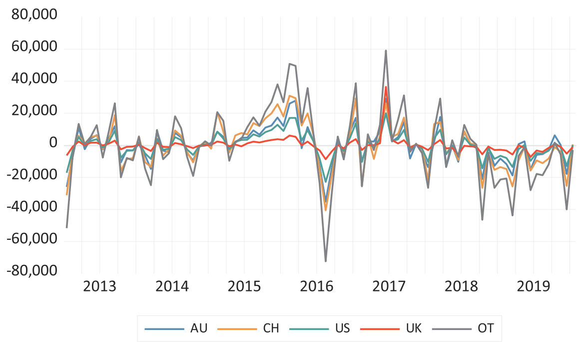

Fig. 4. Cyclical components: short-term co-movement.

Table 5
Correlations: observed data, cycles, and trends.

	AU	CH	US	UK	OT
AU	0.28	0.93	0.98	0.75	0.97
CH	1.00	0.15*	0.98	0.68	0.96
US	1.00	1.00	0.69	0.76	0.99
UK	1.00	1.00	1.00	−0.09*	0.75
OT	1.00	1.00	1.00	1.00	0.46
Std. deviations (cycles)	11,206	14,193	7582	4864	22,591

In the top panel, the numbers above the main diagonal (in blue) are correlations between the cycles, below the main diagonal (in green) are correlations between the trend components, and along the main diagonal are the correlations between the trends and the observed time-series; * indicates insignificance at 5%.

are > 0.95. However, the correlations of the cyclical component of the UK with those of Australia, China, and the US are 0.75, 0.68, and 0.76, respectively. Collectively, the correlations and the graphs suggest strong comovement amongst the cycles in tourism demand of different countries. Thus, we conclude that they respond similarly to transitory shocks.

Furthermore, based on the standard deviations presented in Table 5, we observe that the volatilities of the cyclical components are markedly different. In the case of the UK, the cyclical component is relatively muted. However, the sharp increase during 2017 stands out: this is associated with the English and Irish Lions rugby tour during June and July of 2017. This event brought many tourists from the UK to New Zealand, causing a spike in VAs. That the cyclical component duly captures this spike indicates that the impact of this sporting event on tourism demand was short-lived, and did not alter the long-term trend of VAs from the UK. This result has important implications for policymakers and industry stakeholders: while one-off or sporadic events may boost tourism demand for a short period, they are unlikely to have a transformative impact on its long-term trajectory. Even though the impact of such events is ephemeral, it often tends to be exaggerated. Therefore, caution should be exercised in calibrating outlays and forming expectations regarding the future stream of revenues based on the impact of such events; investments that are customized to cater to such events may prove to be maladaptive in the long-term.

Similar to that of the UK, the cyclical component of the US is less volatile in comparison with those of Australia, China, and Others. In the case of the latter two, however, the cycles are relatively more volatile and pronounced; this suggests that VAs from China and Others are more responsive to transitory shocks. It bears emphasizing that China, a developing country, is in a markedly different state of economic development relative to Australia, the US, and the UK. Hence, it is conceivable that the pronounced cycles are manifestations of relatively high price and income elasticities of Chinese visitors to New Zealand; in contrast, price and income elasticities for VAs from Australia, the US, and the UK are quite low (Schiff & Becken, 2011). Correspondingly, the cycles of the VAs from these three high-income countries are relatively subdued. It is noteworth that our comovement-based results are directionally consistent with estimates of elasticities derived in previous research.

Figs. 5, 6, 7, 8, and 9 illustrate the trend-cycle decompositions of the individual time-series. In the case of the US, the observed data-series is strongly correlated with the trend component–we characterize it as trend-dominated. In the case of the UK, however, the observed data-series is strongly correlated with its cyclical component. Accordingly, we characterize it as cycle-dominated. The VAs from Australia, China, and Others do not exhibit strong associations with their respective trends or cycles–thus, they are neither trend- nor cycle-dominated.

Clearly, the growth of inbound tourism to New Zealand from China has receded since 2016. Recently, however, to curb the spread of Covid-19, tourists from China were barred from entering New Zealand. Furthermore, as of the writing of this paper, New Zealand has closed its borders to all international visitors. The pandemic will ineluctably take an immense toll on not just the tourism industry in New Zealand but on global tourism. However, despite its profound negative impact, as well as the impending global recession, tourism activities may resume in the medium-term.

Therefore, with an eye to the future, it is important to recall the realities and prognostications that prevailed before the start of the

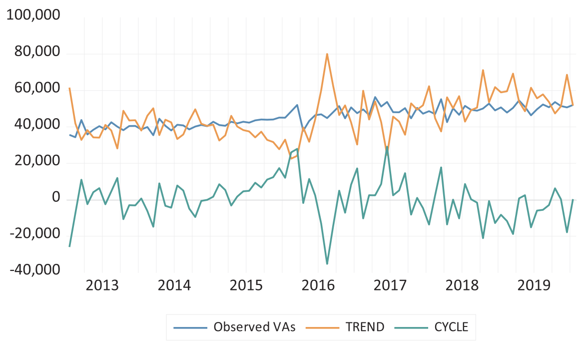

Fig. 5. Australia: trend-cycle decomposition.

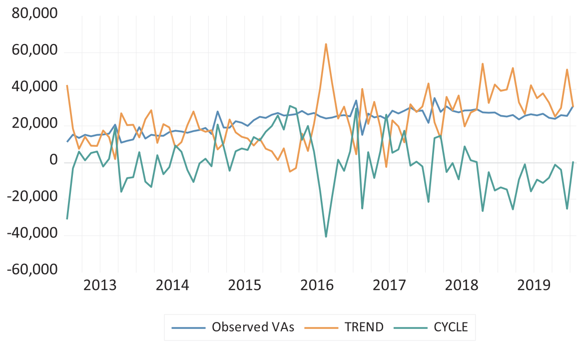

Fig. 6. China: trend-cycle decomposition.

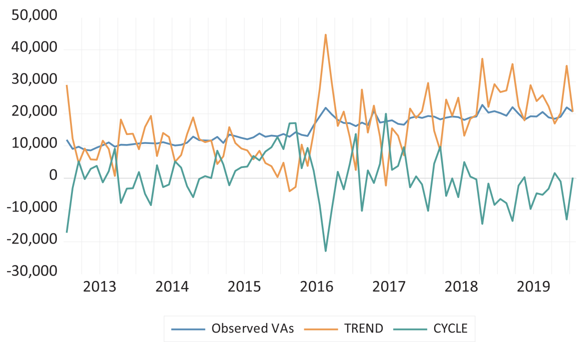

Fig. 7. The US: trend-cycle decomposition.

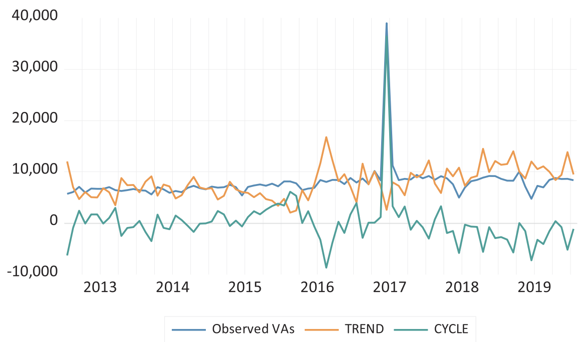

Fig. 8. The UK: trend-cycle decomposition.

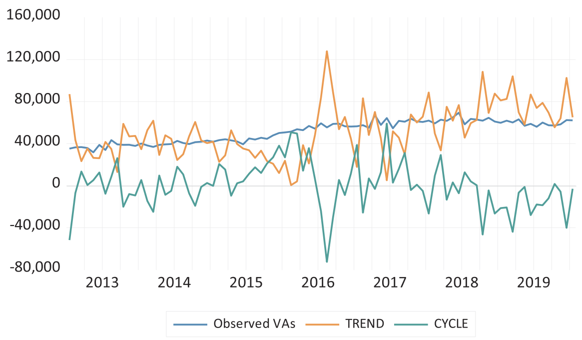

Fig. 9. Others: trend-cycle decomposition.

pandemic: the demand for international tourism in China was on the rise– > 138 million Chinese travelers were expected to make international trips annually by 2020 (Lin, Liu, & Song, 2015). Surely, this has changed; the authors could not have foreseen the onset of the pandemic. Also, there are no longer homogeneous preferences and tendencies typifying Chinese tourists; they can be represented by diverse archetypes (Chen, Dichter, Saxon, Suo, & Yu, 2018). Accordingly, in light of the highly correlated trends and cycles, stakeholders in the tourism industry would benefit from identifying commonalities between the proclivities of tourists from the *four* countries in order to leverage synergies and economies of scale.

Granted that devising policies to attract tourists from countries in the category Others may yield benefits. However, given the small scale of inbound tourism from these countries, the potential benefits may be limited. Accordingly, stakeholders would be well-advised to prioritize the optimization of inbound tourism from the primary tourism-importing countries, which account for almost two-thirds of international tourism in New Zealand: the size and scale of markets are crucial. A simple example clarifies this point: a 1% increase in tourism from Australia would increase the annual number of VAs by 60,000; to achieve a similar result for the number of VAs from Japan, a 90% increase would be needed. Thus, it is important to pursue a multi-pronged approach that formulates policies based on the market-size of tourism-importing countries along with the determinants of, and the comovement amongst tourism demand.

Summary and conclusion

Considering the pivotal role that international tourism plays in New Zealand's economy, we utilize a multivariate trend-cycle decomposition framework to study common trends and common cycles amongst the demand for New Zealand tourism from Australia, China, the US, and the UK; considering the relative insignificance in terms of the volume of inbound tourism from of the rest of the countries, we include them as a group under the category, Others. We find evidence of short- and long-term comovement amongst the tourism demand from the four primary tourism-importing countries as well as Others. Specifically, we find one common trend and four common cycles. The choice of the methodological framework is driven by its aptness to analyze short- and long-term comovement, its usefulness from the perspective of econometric modeling, and by the paucity of the application of multivariate decomposition frameworks in tourism research.

The presence of one common trend and four common cycles allows us to decompose the observed data into their trend and cyclical components. Thus, we are able to construct a detailed view of short- and long-term patterns and, in turn, analyze the degree of short- and long-term comovement in tourism demand. The presence of a single common trend is illuminating: it suggests that, in the long-term, there is a single force that drives the international demand for New Zealand tourism; while country-specific trends may drift apart from one another periodically, they remain tethered to a stable equilibrium in the long-term; also, the trends in long-term tourism demand originating in the four countries (and Others) are proportional and perfectly correlated.

While the cyclical components, which capture the short-term comovement, are not perfectly correlated, they exhibit strong correlations nonetheless. This is especially true for the cyclical components of Australia, China, the US, and Others. However, the correlations between the cyclical component of the UK with those of the other countries are relatively small–to be sure, they are still significant. Furthermore, while the cyclical components of tourism demand from Australia, the US, and (especially) the UK are somewhat muted, those of the tourism demand from China and Others are relatively pronounced. Since cycles capture transitory deviations of the observed data from their respective long-term trends, we conclude that the Chinese tourism demand is more responsive to changes in factors that have a transitory effect. Even though the estimation of elasticities is beyond the scope of this paper, the presence of prominent cycles in the case of China lends credence to the findings in previous analyses, which have revealed higher price and income elasticities of tourism demand in China relative to those in Australia, the US, and the UK.

These results are relevant to business owners, policymakers, and other stakeholders in the tourism industry. Tourism New Zealand, seeking to formulate strategies to re-build the tourism sector in the aftermath of the Covid-19 pandemic, should consider the dichotomy between the short- and long-term associations between tourism demand originating in the different countries to optimize near- and long-term value, enhance regional growth, manage its markets strategically, and work inclusively with industry stakeholders. For example, our results show that, while one-off events–such as the English and Lions rugby tour in 2017– may boost tourism demand in the short-term, their impact is transient. Therefore, such events may not generate sustainable, long-term growth of tourism demand. The potential benefits of such events are often exaggerated and may invoke undue optimism; thus, caution is necessary to avoid myopic investments that are customized to cater to such events, as they may prove to be maladaptive in the long-term.

Also, considering the strong positive correlations between the trends *and* cycles in international tourism demand, identifying proclivities that are common to tourists from various countries, and accordingly designing tourism products and services that appeal to a broad customer base is a prudent approach. Not only would this yield economies-of-scale and help with the prioritization of time- and resource-intensive development initiatives, it would also mitigate potential risks arising from the relatively high sensitivity of tourism demand in China and Others in the short-term. However, scale warrants attention, especially in circumstances in which it is challenging to create initiatives with a broad appeal. Prioritizing initiatives that are targeted towards the primary markets are likely to yield the greatest benefit. For example, in terms of tourism volume, a 1% increase in the number of VAs from Australia is equivalent to a 90% increase in that from Japan; while the former is achievable, the latter seems daunting.

In a world that has become increasingly interconnected, opportunities to examine interlinkages between different facets of tourism abound. However, work in this area is still limited (Song, Dwyer, Li, & CAO, 2012). We advance the scope of time-series modeling in tourism research by demonstrating the application of an alternative approach to examine the short- and long-term interlinkages amongst tourism demand. From an econometric standpoint, our approach has several desirable features: researchers can isolate long-term trends and short-term cycles within a single modeling framework, and thereby eliminate the need to estimate separate models to study long- and short-term comovements; they can study cyclical patterns in non-stationary variables without losing valuable information about the long-term, as variables do not have to be transformed to achieve stationarity; joint treatment of variables that co-move imparts a parsimonious and more informative structure to econometric models, thus, needless coefficients are eliminated while maintaining goodness-of-fit; last but not least, researchers can understand the relative importance of trends and cycles in different time-series simultaneously.

However, it is important to note that within this framework, the decomposition of variables into trends and cycles can be accomplished only in special cases, i.e., when the sum of the number of trends and cycles is equal to the number of variables. Due to the specificity of this criterion, the scope of this approach in terms of time-series decomposition may be limited. Also, the common cycles derived with this method are perfectly synchronized: therefore, the underlying hypothesis may be too restrictive.

While we illustrate the commonalities between trends and cycles, the reasons that underpin the dynamics are not formally identified: this study does not deliver a causal interpretation of tourism dynamics. Nevertheless, comovement in and of itself is worthy of attention: considering that some of the key determinants of tourism demand fall outside the realm of influence for many of the stakeholders in the tourism industry, the knowledge about commonalities amongst trends and patterns in tourism demand may inform business policies. In contrast to some causal econometric models, which can be esoteric and difficult to interpret for many stakeholders, one of the strengths of the reductionist comovement-centric perspective is its simplicity; hence, stakeholders may be amenable to leveraging it in the decision-making process. Importantly, when used complementarily, the two classes of models, i.e., causal and time-series, may provide deep insights into the trends and patterns of tourism demand. The inexactitude of social sciences calls for a policy framework that considers multiple perspectives.

In this paper, we present a New Zealand-specific case-study, not a generalized view of tourism demand. We propose that further research be conducted using this framework to understand theoretical models and empirical regularities that imply the presence of common trends and cycles amongst tourism-related time-series for different regions; inter-sectoral linkages in the context of tourism may also be explored within this framework. Furthermore, the results obtained from univariate decomposition frameworks should be compared with those obtained from multivariate models–this would reveal important insights into the suitability of different modeling techniques to test different hypotheses.

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