Annals of Tourism Research xxx (xxxx) xxx

Contents lists available at ScienceDirect

Annals of Tourism Research

journal homepage: https://www.journals.elsevier.com/annals-of-tourism-research

Research note

Seasonality and cycles in tourism demand—redux

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ARTICLE INFO

Article history:
Received 9 September 2020
Received in revised form 15 November 2020
Accepted 19 November 2020
Available online xxxx

Associate editor: Haiyan Song

Keywords:
Time-series
Cycles
Seasonality
Tourism demand

Analyzing tourism demand cycles is of strong interest to researchers and forecasters. However, often the preponderance of seasonality encumbers the derivation of cycles that are free of seasonal patterns. Using recent advances in time-series econometrics, we offer a solution. We employ two methods that produce cycles that are robust to seasonal properties of the data; cycles from seasonally adjusted and unadjusted data are virtually indistinguishable.

Time-series comprise four latent sub-components: the seasonal component, cycles, trends, and an irregular term. In tourism demand time-series, however, seasonality predominates. Even with a casual glance at tourism demand time-series, such as the number of international visitor arrivals, one can spot recurring seasonal patterns. And veiled behind the salient seasonal ebb and flow are tourism demand cycles—these can last several years and can be influenced by non-seasonal factors such as business cycles, currency exchange rates, money supply, marketing initiatives, and terrorism. The third of the four constituents of tourism demand time-series is the long-term trend, which is also relatively easy to spot. For example, globally, tourism demand has risen during the last four decades, an assertion that we can make by merely observing the global tourism demand curve's upward slope.

Considering that trends and seasonality are conspicuous, the researcher is left with the problem of identifying the cyclical component of tourism demand. This note offers a solution. As such, the principal objective of this note is to utilize recent advances in time-series econometrics to demonstrate two straightforward and effective methods for isolating tourism demand cycles from observed time-series. The simplicity of these methods is perhaps their most desirable feature. Thus, practitioners, analysts, policymakers, and students of tourism demand, who may not have access to statistical software, may not have the requisite training in time-series econometrics, or both, can use these methods to inform business decisions, policy, and understanding of tourism demand. In essence, we provide a novel and easy-to-use approach to solving an old problem; we hope to help democratize tourism demand analysis.

The latent sub-components of time-series are modeled in three important strands of tourism demand literature: in the first, the emphasis is on *forecasting* tourism demand (see Song et al., 2019); in the second, decomposed data—cycles in particular—are used to study the nexus between tourism demand on the one hand, and money supply, search-engine traffic, exchange rates, and business cycles, on the other; in the third, the very sub-components that are derived are analyzed. The present note is closely aligned with the latter two, in the context of which, various techniques have been employed to *isolate* cyclical components of tourism demand. These include the Hodrick Prescott filter (Cao et al., 2016; Ridderstaat & Croes, 2017), spectral tech-

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https://doi.org/10.1016/j.annals.2020.103105
0160-7383/

niques (Chan & Lim, 2011; Coshall, 2000), wavelet decomposition analysis (Wu & Wu, 2019), ensemble empirical mode decomposition (Li & Law, 2020), seasonal and trend decomposition using Loess, i.e., the STL method (Zhang et al., 2020), and serial-correlation-based common trends and cycles decomposition (Vatsa, 2020).

While it is not possible to explicate these and other techniques in a short note, a few observations on some frequently used techniques are worth mentioning. The Hodrick Prescott filter, which is one of the most common methods for decomposing time-series, yields cycles that have seasonality embedded in them. Therefore, while a smoothed trend can be isolated from the observed time-series, a distinction between the seasonal and the cyclical components is not made. Spectral techniques have similar drawbacks. The analysis conducted by Coshall (2000) is a case in point: using spectral decomposition, he derived cyclical components that had manifest seasonal patterns. Such characterizations of cycles are misleading. Considering that seasonality can account for a significant proportion of variation in tourism demand, it is important to derive cycles that are free of seasonality. Seasonal components, when left embedded in the cyclical component, impart a regular periodicity to the cycles. This belies the well-established notion that cycles are stochastic in nature.

The ensemble empirical mode decomposition method generates intrinsic mode functions of different frequencies. Researchers then select the function that they deem a suitable representation of a cyclical component. For example, Li and Law (2020) chose the intrinsic mode function with an average periodicity of 12 months to characterize cycles, which they used in their forecasting model.

There are several concerns with assuming that cycles have an annual cadence: one year is not long enough to capture cycles, which have durations longer than a year; they do not occur at any predictable cadence, let alone annually; their lengths vary, often notably; and last but not least, cycles are irregular and have a jagged appearance. Nonetheless, a duration of 12 months can duly account for seasonal variations.

Suppose that one considers frequencies that are greater than 12 months. In that case, the cycles become overly smooth, with inflection points lying along smooth transitions from expansionary to contractionary phases—another characteristic that contradicts widely-held views regarding the nature of cycles; cycles are not smooth wave-like patterns. Nevertheless, researchers have the latitude in selecting frequencies somewhat arbitrarily. Consequently, it is conceivable that they make choices that confirm their biases. This has important and often negative implications for the derivation and interpretation of the results.

Now let us consider an alternative that addresses the aforestated concerns straightforwardly. Recently, Hamilton (2018) has proposed a regression-based filter that relies on a few observations to derive cyclical components. Noting that finite samples do not have sufficient information to inform infinite-horizon forecasts, Hamilton focuses on a two-year-ahead forecast instead. This is a reasonable benchmark as information relevant to a two-year horizon is generally available. However, based on theory, empirical regularities, or both, if researchers are interested in examining socio-economic shocks whose effects take longer, say three or four years, to dissipate, they may consider alternate forecast horizons. The intuition is this: gaps between forecasts and actual outcomes are inherent in forecasting endeavors, and these gaps define cycles. In other words, cycles comprise elements of the time-series that cannot be forecast; they are the difference between the actual series and the long-term trend.

Specifically, according to Hamilton (2018), the h-period-ahead forecast for time-series y_t, i.e., y_{t+h}, relies on the recent p values: both h and p are integer multiples of the number of periods in a year. For example, in the case of two-year-ahead forecasts using quarterly (monthly) data, $h = 8(24)$ and $p = 4(12)$. The choice of p is instrumental in removing seasonal patterns from the cyclical components. The formal representation of this idea is presented in Eq. (1):

$$y_{t+8} = \alpha_0 + \alpha_1 y_t + \alpha_2 y_{t-1} + \alpha_3 y_{t-2} + \alpha_4 y_{t-3} + v_{t+8} \tag{1}$$

Upon adjusting the time periods in Eq. (1), it can be re-written as

$$y_t = \alpha_0 + \alpha_1 y_{t-8} + \alpha_2 y_{t-9} + \alpha_3 y_{t-10} + \alpha_4 y_{t-11} + v_t \tag{2}$$

The residuals from Eq. (2),

$$\hat{v}_t = y_t - (\hat{\alpha}_0 + \hat{\alpha}_1 y_{t-8} + \hat{\alpha}_2 y_{t-9} + \hat{\alpha}_3 y_{t-10} + \hat{\alpha}_4 y_{t-11}) \tag{3}$$

characterize the cyclical component, insofar as the cycles are defined as the deviation of the trend from the observed data; to be clear, they also comprise the irregular term, which is both stationary and unforecastable. This is in contrast to the STL method, which removes the irregular term and the seasonal component but leaves the cycles embedded within the trend: the latter is non-stationary.

Hamilton's filter requires only four recent observations to derive the cycles. Furthermore, given the regression's autoregressive nature, no other variables are needed to isolate the cyclical component; one need not have the correct model to undertake this exercise.

Next, consider a simple and quick robustness check proposed by Hamilton (2018); its ease-of-execution is noteworthy. This check rests upon the assumption that the time-series are random walk processes, which, apropos of economic time-series, is another stylized fact that can be easily verified by conducting unit-root tests. Given this property, the time-series, say y_t, can be represented as follows:

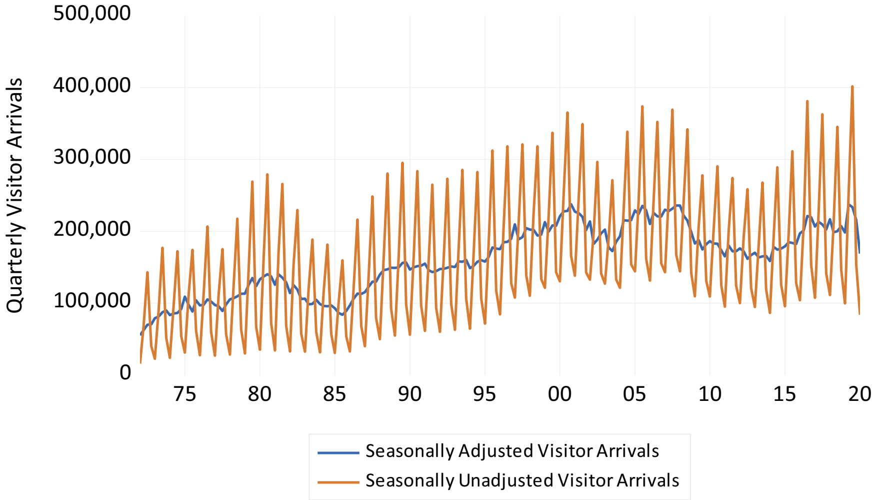

Fig. 1. Seasonally adjusted and unadjusted visitor arrivals from the United Kingdom to Canada.

$y_t = y_{t-1} + \epsilon_t$, where ϵ_t is the white-noise disturbance term. Given that there are eight quarters in two years, the filtered series can be obtained as the difference between y_{t+8} *and* y_t, i.e.,

$$\hat{v}_{t+8} = y_{t+8} - y_t \tag{4}$$

Thus,

$$\hat{v}_t = y_t - y_{t-8} \tag{5}$$

Eq. (5), which closely approximates the cyclical component derived from Eq. (3), can be solved using any spreadsheet software such as Microsoft Excel.

An empirical illustration to bring the above methods to life follows. We use quarterly seasonally unadjusted data for the period 1972Q1–2020Q1 on visitor arrivals from the United Kingdom to Canada. The data are obtained from the Statistics Canada website.

Visually inspecting the data makes a good starting point. Fig. 1 shows the seasonally unadjusted and seasonally adjusted time-series; the latter is obtained by applying the United States Census Bureau's X-13 seasonal adjustment method to the former. It is natural to ask, why consider both data types? There are two important reasons. One, seasonality can account for a substantial proportion of the variance in tourism demand. Therefore, it is important to call attention to the prominence of seasonality and show how it can mask cycles. Two, we want to show that both of the aforestated methods generate cycles that do not exhibit recurring seasonal patterns; the cycles are robust to the data's seasonal properties.

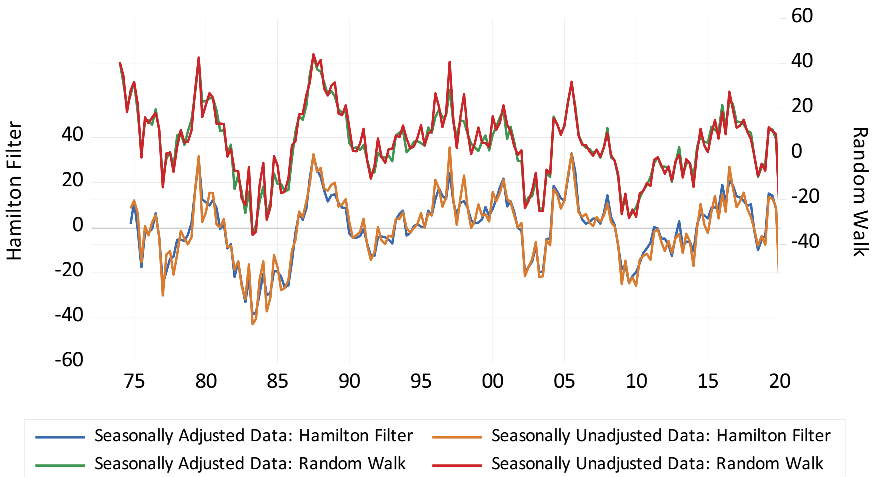

Fig. 2. Cyclical components – Hamilton filter and random walk model.

Table 1
Descriptive statistics and correlations amongst cycles.

	S.A. IVAs HF	S.U. IVAs HF	S.A. IVAs RW	S.U. IVAs RW
Panel A				
Mean	−0.00	−0.00	4.46	5.06
S. deviation	13.99	14.69	15.68	16.10
Panel B				
S.A. IVAs HF	1.00			
S.U. IVAs HF	0.97	1.00		
S.A. IVAs RW	0.91	0.91	1.00	
S.U. IVAs RW	0.88	0.93	0.97	1.00

Note: HF (RW) denotes Hamilton filter (random walk); S.A. (S.U.) denotes seasonally adjusted (seasonally unadjusted) data; IVAs denotes international visitor arrivals; correlations are presented in Panel B.

Expectedly, seasonality is evident in the seasonally unadjusted visitor arrivals; the sawtooth pattern, which is familiar to tourism researchers, typifies tourism demand—it is not an artefact of the data-series chosen for this study. Furthermore, the X-13 seasonal adjustment method duly removes this pattern. Therefore, one may surmise that the seasonally adjusted time-series comprises only cycles and the long-term trend. While the two time-series look markedly different, the only difference between the two is the presence or the absence of seasonality. Thus, it is reasonable to assume that the cyclical components of the two series should bear strong resemblance to one another. However, is this the case?

Fig. 2 shows that this is indeed the case: the cycles obtained from the seasonally adjusted and unadjusted data are virtually indistinguishable. Moreover, the random walk model in Eq. (5) produces results that closely resemble those produced by the Hamilton filter. The correlations in the bottom panel of Table 1 corroborate these visual observations; the correlations are high, positive, and significant in each case. Also, the standard deviations of the four series are similar. However, the means of the cycles produced by the random walk model are larger than those produced by the Hamilton filter. This difference is due to the absence of a constant in Eq. (5) and its presence in Eq. (3).

Considering the preponderance of seasonality in tourism demand data, in conjunction with the ability of the Hamilton filter and the random walk model to produce cycles that are devoid of seasonal patterns and robust to seasonal properties of the data, researchers and analysts seeking to examine tourism demand cycles would find these methods useful. These methods can be applied to decompose and examine the associations between broad classes of tourism demand and economic time-series. In future research endeavors, we will utilize these methods to study associations between tourism demand and macroeconomic time-series—these methods lend themselves particularly well to such analyses.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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