# SEA SURFACE TEMPERATURES: SEASONAL PERSISTENCE AND TRENDS

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## ABSTRACT

This paper deals with the analysis of the sea surface temperatures using a reconstructed dataset which goes back to 1884, with a monthly time frequency. We use fractional integration methods to examine features such as persistence, seasonality and time trends in the data. The results show that seasonality is a relevant issue finding evidence of seasonal unit roots. Removing the seasonal component, persistence is also very significant, and looking at the data month by month, evidence of significant linear trends is detected in all cases. According to these results, monthly sea surface temperatures increase between 0.07ºC and 0.11ºC every 100 years.

**Keywords:** Sea surface temperatures; seasonality; time trends; persistence

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## 1. Introduction

The interest in global warming and climate change has increased rapidly in recent years. There is agreement that the Earth's surface temperature has increased over the last 100 years by between ∼0.3℃ and ∼0.6℃. (Houghton et al., 1995; Cane et al, 1997; Hansen and Lebedeff, 1988; Nicholls et al., 1996; Jones et al., 2010; Folland et al., 2018). The causes of this temperature increase may be a response to anthropogenic forcing (industrialization and the effect of burning and emissions of fossil fuel, greenhouse gas concentration that affects the atmosphere, etc.), a part of the climate system's innate natural variability (e.g. solar irradiance), or a combination of the two. However, most of the scientific community mantains an almost unanimous agreement on this topic supporting the anthropogenic origin of climate change (Anderegg et al., 2010; Beckage et al. 2018).

The surface air temperature is considered as the usual variable to determine climate change and many articles have investigated the presence of time trends in air temperatures either at a global level (Santer et al. 1995; Hegerl et al. 1996, 1997; Jones and Hegerl 1998, Hansen et al., 2010; etc.) or at a local and regional temperatures (Ghil and Vautard 1991; Hasselmann 1993; Schlesinger and Ramankutty 1994; North and Kim 1995; North et al. 1995; Papalexiou et al., 2018; etc.).

However, sea surface temperature (SST) is a fundamental physical parameter for the understanding of climate dynamics and climate change due to the oceans' large thermal inertia compared with that of the atmosphere and land (Deser et al., 2010).

In this research we focus on understanding sea surface temperatures and their behaviour with a monthly time frequency. This paper is a contribution to the literature on the analysis of sea surface temperature from a time series viewpoint focusing on some its features such as seasonality, time trends and persistence. To this purpose, we examine the time series properties of sea surface temperatures from January 1884 to January 2019 using monthly data. Another contribution of this work is that by the first time we jointly examined the three features (time trends, persistence and seasonality) in a unified treatment based on long memory and fractional integration, which has not been jointly studied so far in SST data. The dataset was obtained from KNMI Climate Explorer which is a web application to analysis climate data statistically. This tool is made available by the World Meteorological Organization together along with the European Climate Assessment & Data.

The rest of the paper is organized as follows: In Section 2 we briefly review the literturautre on sea surface temperatures. In Section 3 we present the techniques used in the paper. Section 4 describes the dataset, while Section 5 contains the empirical results. Finally, Section 6 concludes the paper.

## 2. Sea surface temperatures

Temperatures of the sea surface are used as a key factor connecting the oceans to the global climate system. An example of this affirmation is collected in the research done by Yaya and Akintande (2018) that relates global and regional sea surface and land air surface temperatures finding evidence of a high correlation between them. Also, SST anomalies in the tropical Pacific are commonly used indicators for diagnosing the El Niño–Southern Oscillation (ENSO) state, and the impact of global warming on SST based ENSO monitoring indices have been analysed recently (Turkington et al. (2018)).

SST might present certain irregularities and its potential non-linear pattern creates difficulties to measure it. Nevertheless, reliable data can be found at the Hadley Centre (Rayner et al., 2003; 2006; 2009; Minobe and Maeda, 2005; etc.), and also at the National

Oceanic and Atmospheric Administration (Smith et al., 2008), and in Kaplan et al. (1998) among other sources.

One of the main assumptions regarding the classical definition of temperature anomalies is that the annual cycle is constant and does not change over time. In order to analyse the SST anomalies, several statistical methods have been used, such as, optimal smoothing (OS), the Kalman filter (KF) and optimal interpolation (OI) (Kaplan et al., 1998). However, more accurate data, achieved by including bias-adjusted satellite data, and accurate analysis is required to minimize errors (Smith, 2008; Banzon, 2016).

On the other hand several authors have claimed that the climate system presents memory or persistence across different regimes. In 2003, Gil-Alana introduced fractional integration techniques to analyse the Central England Temperature (CET) from 1659 to 2001, which is the longest available instrumental record of temperature in the world. The results show that central England temperatures have increased about 0.23 °C per 100 years in recent history (Gil-Alana, 2003). Also, he evaluated the warming in both the Northern and Southern Hemispheres (Gil-Alana, 2005, 2007). Other authors that have also found persistence and evidence of long memory in temperatures and sea temperatures are Eichner et al. (2003), Lennartz and Bunde (2009), Franzke (2012a, 2013), Bunde et al. (2014), Ludescher et al. (2016), Massah and Kantz (2016), Deng et al. (2018) among many others. On the other hand, Álvarez-Ramirez (2008) showed that ocean temperatures are more persistent than land temperatures and several authors have studied recently the SST locally, in different areas, for instance, in the Mediterranean Sea (Shaltout, 2014), Baltic Sea (Stramka and Bialogrodzka 2015), Southwest coast of Portugal (Goela, 2016), pointing at a general increasing of the local temperature, hence contributing to global warming (Mudelsee, 2019). Interestingly, Breaker (2019) has recently estimated long-range persistence in ocean surface temperature off the coast of central California, a region where similar observations had not been made. Other papers which analyze time structure dependencies and dynamics in temperatures are Stern and Kaufmann (2000), Kaufmann and Stern (2002), Jones and Moberg (2003), Gil-Alana (2003, 2005), Moberg et al. (2005), Mills (2004, 2006, 2007), Gil-Alana (2008a, 2015), Deng et al. (2018) and Yaya and Akintande (2018).

## 3. Methodology (Explain in an easier way)

As the main goal in the paper is to show if there is a linear trend in the sea surface temperatures across the years, our initial model is based on the following regression,

$$y_t = \alpha + \beta t + x_t; \qquad t = 1, 2, ..., \tag{1}$$

where $y_t$ refers to the observed data, i.e., the anomalies over sea surface temperatures, $\alpha$ and $\beta$ are unknown coefficients which refer respectively to a constant and a potential linear trend in time, and $x_t$ is the error term (or the detrended series) that is supposed to be well-behaved. Thus, for example, if this error term in (1) is a random variable independently and normally distributed with mean zero and a constant variance, the ordinary least squares (OLS) estimate of $\beta$ can be obtained, and statistical inference based on the classical F and t statistics can be applied here (Hamilton, 1994). Thus, if we are able to reject the null hypothesis of:

$$H_o = \beta = 0, \tag{2}$$

versus the alternative:

$$H_a = \beta > 0, \tag{3}$$

we can then claim that temperatures are increasing over time. Nevertheless, a pattern that is observed in monthly sea surface temperatures is that they display several features which are not consistent with standard models, for example, seasonality, along with strong dependence between the observations across time.

Following Hyllerberg (1986, 1992) seasonality can be defined as a systematic, though not necessarily regular, variation around trend in time series. This author classifies seasonality in three categories when modelling seasonal data: i) purely deterministic models (by means of seasonal dummy variables), ii) seasonal stochastic stationary models (using seasonal ARMA processes), and iii) seasonal nonstationarity (by means of seasonal differences). The first group based on seasonal dummies simply allows for the mean of the series to vary by season, and therefore it raises no statistically interesting issues. Therefore, in the empirical application carried out below we use stochstic approaches using first a simple autoregressive of order 1 (AR(1)) process of the form:

$$u_t = \varphi u_{t-12} + \varepsilon_t, \qquad t = 1, 2, \ldots \tag{4}$$

assuming so far that $x_t = u_t$, and where $\varepsilon_t$ is a white noise process. Thus, $\varphi$ indicates the degree of seasonal serial dependence.[1] If non-seasonal dependence is also permitted, we can add the following model,

$$(1 - L)^d x_t = u_t, \quad t = 0, \pm 1, \ldots, \tag{5}$$

with $x_t = u_t = 0$ for $t \leq 0$, where L indicates the lag operator, i.e., $L^k x_t = x_{t-k}$, and d can be any real value. Clearly, if $d = 0$, $x_t = u_t$, there is no dependence at all, and the classical estimation of $\beta$ in (1) and based on ordinary (OLS) or generalised (GLS) least squares still remains valid. However, allowing for $d > 0$, dependence is permitted, and the higher the value of d is, the higher the level of dependence between the observations is, noting that the polynomial on the left hand side of equation (5) can be expressed, for all real d, as:

$$(1 - L)^d = \sum_{j=0}^{\infty} \psi_j L^j = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j L^j = 1 - d\,L + \frac{d\,(d-1)}{2} L^2 - \ldots,$$

[1] In the empirical application carried out in Section 5, the seasonal AR parameter is found to be very close to 1, suggesting the need of seasonal differentiation. In fact, performing seasonal unit root tests the results support this hypothesis in all series.

and thus, equation (5) can be expressed as:

$$(1-L)^d x_t \;=\; x_t \;-\; d\,x_{t-1} \;+\frac{d\,(d-1)}{2}\,x_{t-2} \;-\; \ldots \;+\; u_t..$$

Then, it is said that $x_t$ is integrated of order d and denoted as I(d). This type of process displays the property of long memory because of the strong degree of association between observations which are far distant in time. They were introduced in the earlier 80s by Granger (1980, 9181), Granger and Joyeux (1980) and Hosking (1981) and since then have been widely employed in the analysis of aggregate data including climatological and meteorological data (Bloomfield, 1992; Koscielny-Bunde et al., 1998; Percival et al., 2001; Monetti et al., 2003; Gil-Alana, 2005, 2008b, 2015, 2018; Rybski et al., 2006, 2008; Fatichi et al., 2009; Franzke, 2010, 2012b; Bunde et al., 2014; Yuan et al., 2015; Ludescher et al., 2016; Bunde, 2017 among many others). In this context of fractional integration, the estimation of β in (1) must take into account the additional dependence structure on the error term.

We estimate the model by using the Whittle function in the frequency domain (Dahlhaus, 1989). The Whittle function is an approximation to the likelihood function, and we use this function in the context of a testing procedure developed in Robinson (1994) that is very convenient with our dataset. This method allows us to test the null hypothesis:

$$H_o \;=\; d \;= d_o, \qquad (6)$$

for any real value $d_0$, in a model given by (1) and (5) independently of the specification of $u_t$ in (5), which may be a seasonal AR(1) process as in (4). The test statistic has a standard null N(0, 1) limit distribution and is the most efficient method in the Pitman sense against local departures from the null. Moreover, this standard behaviour holds for any value of $d_0$, including thus stationary ($d_0 < 0.5$) and nonstationary ($d_0 \geq 0.5$) hypotheses.

## 4. Data

The data examined in this work are the anomalies over sea surface temperatures, and have been obtained from the KNMI Climate Explorer[2], which is part of the World Meteorological Organization, and from the European Climate Assessment & Data. The monthly time period examined stretches from January 1884 to January 2019.

**[Insert Figures 1 and 2 about here]**

Figure 1 plots the original data of sea surface temperature time series downloaded from KNMI webpage. As can be observed, there are periods of time where the information is incomplete. For this reason, first we have analyzed the time periods where we have complete data (see Figure 2, Panel i), with data starting in 1947. Then, we have also linearized the time series with the purpose of being able to analyze periods of longer duration in the data (see Figure 2, Panels ii) (starting in 1922), iii) (in 1904) and iv) (in 1884).[3]

## 5. Results

Based on the monthly nature of the data, we start by using the model given by the equations (1), (4) and (5), i.e.,

$$y_t = \alpha + \beta t + x_t, \quad (1 - L)^d x_t = u_t, \quad (1 - \varphi L^{12}) x_t = \varepsilon_t, \qquad (7)$$

testing $H_o$ (6) for $d_o$-values equal to 0, 0,01, … (0.01), …, 1.99, and 2. As earlier mentioned, this parameter is very relevant in the sense that it is informing us about the degree of dependence in the data and thus, it can be taken as an indicator of the level of persistence. Higher the differencing parameter is, higher the level of persistence is.

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[2] https://climexp.knmi.nl/select.cgi?id=someone@somewhere&field=coads_sst

[3] All reconstructations are based on linear extrapolation using the last observation prior to the break and the first one after the break.

**[Insert Table 1 about here]**

We conduct the estimation of $d_o$ under three different set-ups: i) with no deterministic terms, i.e. assuming that $\alpha = \beta = 0$ in (7); ii) with an intercept, i.e., imposing $\beta = 0$, and iii) with an intercept and a linear time trend, i.e., estimating $\alpha$ and $\beta$ along with the other parameters in the model. We selected the appropriate models by using their corresponding t-values and the results showed that the time trend is not required in any of the four series, the intercept being sufficient to describe the deterministic components. The results of the estimated coefficients are reported in Table 1. The estimated values of d are 0.73 for the sample starting in 1884; 0.74 for the one starting in 1904, and slightly higher (0.81 and 0.86) for those starting in 1922 and 1947. If we look at the confidence intervals, we see that all values belong to the interval [0.5, 1), implying nonstationary mean reverting behaviour. However, if we focus on the seasonal AR coefficients, we see that they are all very close to 1, suggesting that the series may contain seasonal unit roots.

Based on these high seasonal AR coefficients, we next conducted seasonal unit root tests (based on Dickey, Hasza and Fuller (DHF, 1984), Beaulieu and Miron (BM, 1993) and Hylleberg et al. (HEGY, 1990) methods), and the results, though not reported, suggested evidence of unit roots in the four series.[4] Thus, we perform seasonal first differences, and work next with the differenced series. Here, noting that seasonality has been removed, we consider the model given only by the equations (1) and (4), i.e.,

$$y_t \;=\; \alpha \;+\; \beta t \;+\; x_t, \qquad (1 \;-\; L)^d\, x_t \;=\; u_t, \quad t \;=\; 1, 2, \dots, \qquad (7)$$

Under the assumptions that $u_t$ is both white noise, i.e., $u_t = \varepsilon_t$, and autocorrelated. However, in the latter case, instead of imposing a particular parametric (ARMA) structure

[4] The same evidence in favor of seasonal unit roots was obtained when using seasonal fractionally integrated methods (see, Gil-Alana and Robinson, 2001).

on $u_t$, we use a non-parametric approach due in Bloomfield (1973) which approximates ARMA models with very few parameters.[5]

**[Insert Table 2 about here]**

Table 2 (Panel i) displays the estimates under the assumption of white noise errors, while Panel ii) focuses on the case of autocorrelation. The values are very similar in the two cases, and the first thing we observe is that the time trend is not required in any single case. The estimates of d are large, though smaller than 1 in all cases, with the exception of the dataset starting in 1947 with autocorrelated errors. These results indicate that the data are highly persistent but no evidence of time trends is detected on the data.

**[Insert Table 3 about here]**

As a final step in the analysis, we focus on the data separated by months, testing once more the degree of persistence and the significance of the time trend coefficients in the model given by (7) for the two types of residuals (uncorrelated and following the model of Bloomfield). The results for the reconstructed dataset starting in 1884 are presented in Table 3. The first thing we observe is that all estimated values of d are positive and smaller than 1 implying, once more, fractional integration. The values range between 0.43 (March with autocorrelation) and 0.66 (October with no autocorrelation. However, the most interesting feature is that the time trend coefficients are now statistically significant in all cases, implying an increase in the temperatures during the sample period. Under no autocorrelation, the highest increases take place in March (0.085) and April (0.083) implying an increase of about 0.8ºC in the temperatures every 100 years and a very similar result is obtained under autocorrelated errors.

**[Insert Tables 4 – 6 about here]**

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[5] Non-linear deterministic terms of the form advocated by Cuestas and Gil-Alana (2016) were also employed but the coefficients were found to be statistically insignificant in all cases.

Tables 4, 5 and 6 display the results for the subsamples starting respectively at 1904, 1922 and 1947. For the first two of these subsamples, the estimated values of d are very similar to those in Table 3 (with values of d ranging from 0.24 to 0.57), however, the time trend coefficients are much higher than those in Table 3, with values above 0.010 in practically all cases, implying increases above 0.10ºC/100 years for each month of the year. Finally, in Table 6, the results refer to the observed data between 1947 and 2018. Here, the values of d are much smaller than in the previous cases, ranging from 0.12 to 0.46 with no autocorrelation and being much smaller with the model of Bloomfield. In fact, the I(0) hypothesis of short memory (i.e., d = 0) cannot be rejected in eight of the months, and long memory patterns are only detected in the months of July, August, September and November. Nevertheless, the time trend coefficients are once more statistically significant in all cases, with values close to those given for the whole sample period (1884 – 2018).

These results are in line with other researches done for Sea Surface Temperature in the Mediterranean zone (see Pastor et al., 2019). They conclude that there is a consistent warming trend for the Mediterranean in the period 1982-2016, finding different linear trends for seasons and months. Alexander et al. (2018) conclude that the warming trend projected in their research occurs in summer affecting positively (from 0.05 to 0.5°C/decade) in the range of temperatures. The findings achieved by this research are consistent with many other studies (see Friedland and Hare, 2007; Chollett et al., 2012; López García and Belmonte, 2011; Shaltout and Omested, 2014; Thomas et al., 2017).

## 6. Conclusions

In this article we have examined the sea surface temperatures using a reconstructed dataset which goes back to 1884, with a monthly time frequency. We use fractional integration techniques to investigate issues such as the degree of persistence in the data, the seasonality and the presence of time trends. This specification is more general than other standard methods and include the classical stationarity I(0) and nonstationarity I(1) as particular cases of interest. Our results indicate first that seasonality is a very relevant issue in the data and testing for seasonal unit roots, the results provide strong evidence in favour of this hypothesis. Removing the seasonal component, throughout seasonal differentiation, the data are still very persistent and significant trends are observed across different sample periods. We provide evidence that the temperatures have increased between 0.07ºC and 0.11ºC during the last one hundred years.

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**Figure 1: The monthly time period analysed is from January 1884 to January 2019**

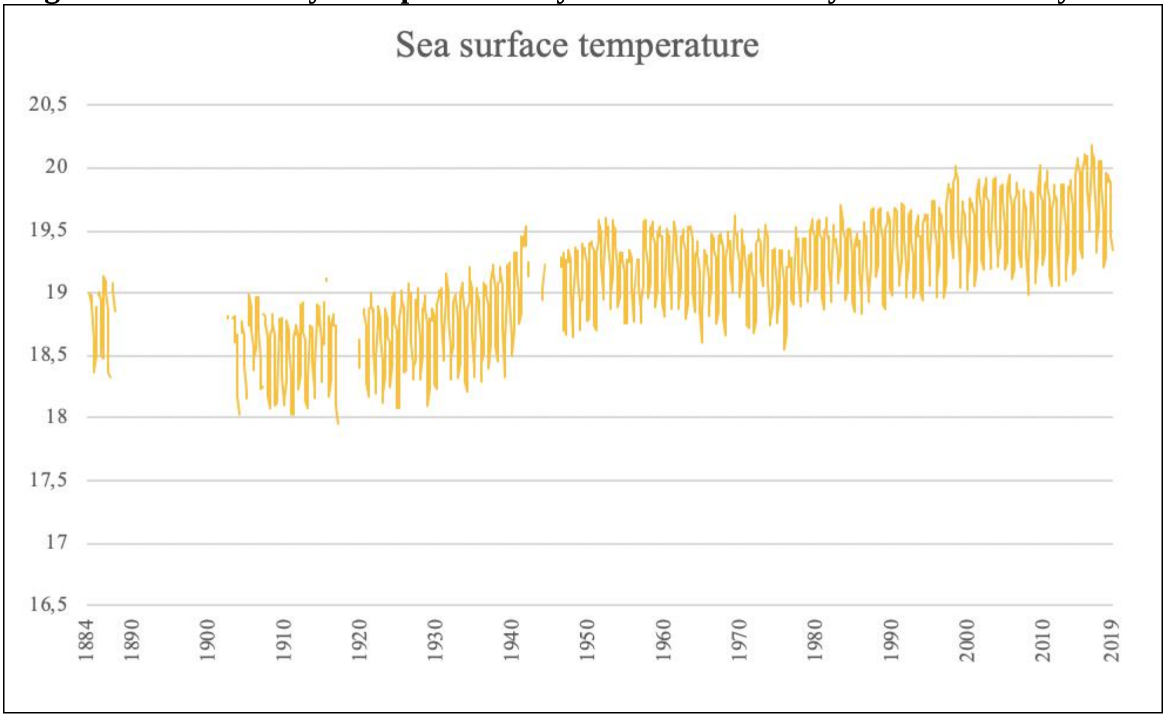
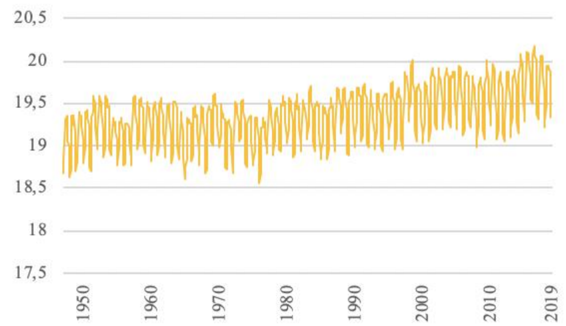
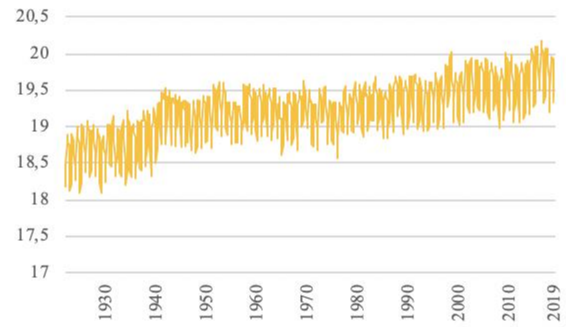


**Figure 2: Time series plots. Sea Surface Temperatures**

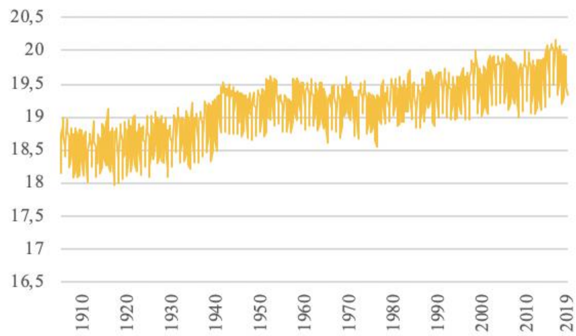
i) Sea Surface Temperatures 1947 -2019




ii) Sea Surface Temperatures 1922 -2019




iii) Sea Surface Temperatures 1904 -2019




iv) Sea Surface Temperatures 1884 -2019

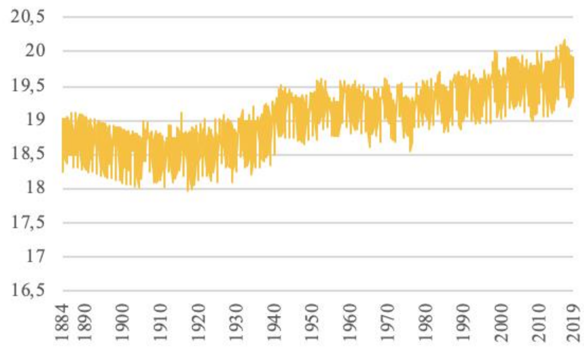


**Table 1: Estimated coefficients in the model given by equation (7)**

| i) with no autocorrelation | | | | |
|---|---|---|---|---|
| Series | d (95% band) | Intercept | Time trend | Seas. |
| 1884 – 2018 | 0.74 (0.69, 0.78) | 18.366 (107.19) | ---- | 0.917 |
| 1904 – 2018 | 0.75 (0.70, 0.80) | 18.368 (110.40) | ---- | 0.916 |
| 1922 – 2018 | 0.81 (0.76, 0.86) | 18.275 (109.89) | ---- | 0.922 |
| 1947 – 2018 | 0.86 (0.81, 0.92) | 18.765 (116.07) | ---- | 0.923 |

The values in parenthesis in the third column are t-values. Thus, values above 1.645 in absolute value indicate statistical significance at the 5% level.

**Table 2: Estimated values of d on the first seasonal differences**

| i) with no autocorrelation | | | |
|---|---|---|---|
| Series | No terms | With intercept | With time trend |
| 1884 – 2018 | 0.73 (0.69, 0.77) | **0.73 (0.69, 0.77)** | 0.73 (0.69, 0.77) |
| 1904 – 2018 | 0.74 (0.70, 0.79) | **0.75 (0.70, 0.79)** | 0.75 (0.70, 0.79) |
| 1922 – 2018 | **0.79 (0.75, 0.83)** | 0.79 (0.75, 0.84) | 0.80 (0.75, 0.84) |
| 1947 – 2018 | **0.85 (0.80, 0.91)** | 0.86 (0.81, 0.91) | 0.86 (0.81, 0.91) |
| ii) with autocorrelation | | | |
| Series | No terms | With intercept | With time trend |
| 1884 – 2018 | 0.82 (0.69, 0.90 | **0.81 (0.71, 0.89)** | 0.81 (0.71, 0.89) |
| 1904 – 2018 | 0.79 (0.69, 0.91) | **0.80 (0.70, 0.90)** | 0.80 (0.70, 0.90) |
| 1922 – 2018 | **0.86 (0.75, 0.99)** | 0.85 (0.76, 1.00) | 0.85 (0.76, 1-00) |
| 1947 – 2018 | **0.99 (0.87, 1.15)** | 1.02 (0.86, 1.16) | 1.02 (0.86, 1.16) |

The values in parenthesis indicate the 95% confidence band for the values of d; in bold the selected model for each series.

**Table 3: Seasonal persistence and trends with sample size: 1884 - 2018**

| Month | i) No autocorrelation | | ii) With autocorrelation | |
|---|---|---|---|---|
| January | 0.55 (0.45, 0.67) | 0.0078 (5.20) | 0.54 (0.37, 0.74) | 0.0078 (5.14) |
| February | 0.63 (0.52, 0.77) | 0.0071 (3.38) | 0.54 (0.36, 0.78) | 0.0071 (4.57) |
| March | 0.58 (0.46, 0.73) | 0.0085 (5.25) | 0.43 (0.25, 0.66) | 0.0086 (8.01) |
| April | 0.55 (0.46, 0.68) | 0.0084 (6.36) | 0.53 (0.36, 0.76) | 0.0084 (6.34) |
| May | 0.63 (0.54, 0.76) | 0.0073 (4.41) | 0.62 (0.48, 0.79) | 0.0073 (4.46) |
| June | 0.60 (0.50, 0.76) | 0.0076 (5.30) | 0.52 (0.36, 0.69) | 0.0077 (6.78) |
| July | 0.58 (0.48, 0.71) | 0.0077 (5.47) | 0.54 (0.38, 0.70) | 0.0078 (6.01) |
| August | 0.61 (0.52, 0.75) | 0.0075 (4.91) | 0.54 (0.38, 0.71) | 0.0076 (6.16) |
| September | 0.62 (0.52, 0.75) | 0.0076 (5.07) | 0.65 (0.45, 0.85) | 0.0075 (4.34) |
| October | 0.66 (0.55, 0.80) | 0.0075 (3.73) | 0.58 (0.36, 0.80) | 0.0077 (5.00) |
| November | 0.56 (0.46, 0.67) | 0.0077 (4.92) | 0.63 (0.44, 0.87) | 0.0077 (3.65) |
| December | 0.44 (0.36, 0.55) | 0.0082 (7.70) | 0.63 (0.44, 0.80) | 0.0077 (3.57) |

The values in parenthesis in the $2^{nd}$ and $4^{th}$ columns indicate the 95% confidence band for the values of d; those reported in columns $3^{rd}$ and $5^{th}$ are t-values.

**Table 4: Seasonal persistence and trends with sample size: 1904 - 2018**

| Month | i) No autocorrelation | | ii) With autocorrelation | |
|---|---|---|---|---|
| January | 0.46 (0.35, 0.1) | 0.0100 (7.44) | 0.43 (0.25, 0.68) | 0.0101 (7.17) |
| February | 0.49 (0.34, 0.73) | 0.0084 (5.28) | 0.31 (0.12, 0.72) | 0.0092 (8.91) |
| March | 0.52 (0.40, 0.70) | 0.0100 (6.29) | 0.37 (0.19, 0.62) | 0.0101 (8.63) |
| April | 0.42 (0.31, 0.57) | 0.0104 (9.99) | 0.35 (0.18, 0.61) | 0.0104 (9.55) |
| May | 0.50 (0.37, 0.68) | 0.0103 (8.49) | 0.33 (0.14, 0.57) | 0.0105 (11.28) |
| June | 0.43 (0.30, 0.63) | 0.0103 (10.66) | 0.24 (0.07, 0.44) | 0.0105 (13.67) |
| July | 0.43 (0.31, 0.62) | 0.0100 (9.65) | 0.32 (0.15, 0.63) | 0.0102 (10.82) |
| August | 0.47 (0.35, 0.66) | 0.0103 (9.23) | 0.30 (0.15, 0.51) | 0.0105 (12.05) |
| September | 0.50 (0.38, 0.68) | 0.0105 (8.97) | 0.41 (0.24, 0.71) | 0.0105 (9.68) |
| October | 0.56 (0.42, 0.74) | 0.0106 (6.25) | 0.39 (0.21, 0.64) | 0.0106 (9.16) |
| November | 0.47 (0.36, 0.62) | 0.0106 (7.61) | 0.47 (0.28, 0.79) | 0.0106 (6.77) |
| December | 0.30 (0.21, 0.43) | 0.0107 (12.66) | 0.40 (0.22, 0.66) | 0.0106 (7.55) |

The values in parenthesis in the 2$^{nd}$ and 4$^{th}$ columns indicate the 95% confidence band for the values of d; those reported in columns 3$^{rd}$ and 5$^{th}$ are t-values.

**Table 5: Seasonal persistence and trends with sample size: 1922 - 2018**

| Month | i) No autocorrelation | | ii) With autocorrelation | |
|---|---|---|---|---|
| January | 0.46 (0.35, 0.60) | 0.0108 (6.61) | 0.44 (0.23, 0.70) | 0.0107 (6.25) |
| February | 0.47 (0.34, 0.62) | 0.0104 (5.94) | 0.34 (0.12, 0.58) | 0.0101 (7.33) |
| March | 0.57 (0.43, 0.76) | 0.0107 (4.85) | 0.37 (0.15, 0.65) | 0.0104 (17.66) |
| April | 0.49 (0.36, 0.68) | 0.0110 (7.44) | 0.31 (0.08, 0.60) | 0.0115 (9.28) |
| May | 0.54 (0.39, 0.75) | 0.0117 (6.93) | 0.29 (0.08, 0.59) | 0.0109 (9.86) |
| June | 0.46 (0.32, 0.69) | 0.0112 (8.69) | 0.17 (-0.02, 0.42) | 0.0105 (12.44) |
| July | 0.47 (0.35, 0.65) | 0.0109 (8.14) | 0.36 (0.14, 0.58) | 0.0107 (8.97) |
| August | 0.53 (0.40, 0.72) | 0.0115 (7.31) | 0.31 (0.09, 0.58) | 0.0109 (10.26) |
| September | 0.51 (0.38, 0.69) | 0.0115 (7.67) | 0.42 (0.18, 0.73) | 0.0112 (8.06) |
| October | 0.60 (0.46, 0.80) | 0.0118 (5.10) | 0.44 (0.17, 0.76) | 0.0113 (7.12) |
| November | 0.48 (0.36, 0.64) | 0.0113 (6.56) | 0.57 (0.30, 0.92) | 0.0116 (4.82) |
| December | 0.29 (0.20, 0.42) | 0.0109 (10.64) | 0.43 (0.23, 0.69) | 0.0113 (6.25) |

The values in parenthesis in the 2nd and 4th columns indicate the 95% confidence band for the values of d; those reported in columns 3rd and 5th are t-values.

**Table 6: Seasonal persistence and trends with sample size: 1947 - 2018**

| Month | i) No autocorrelation | | ii) With autocorrelation | |
|---|---|---|---|---|
| January | 0.14 (0.00, 0.35) | 0.0070 (7.75) | 0.01 (-0.25, 0.32) | 0.0060 (8.21) |
| February | 0.18 (0.04, 0.38) | 0.0072 (7.20) | 0.07 (-0.17, 0.38) | 0.0071 (7.30) |
| March | 0.30 (0.16, 0.51) | 0.0076 (6.16) | 0.12 (-0.11, 0.45) | 0.0075 (7.43) |
| April | 0.37 (0.23, 0.60) | 0.0082 (5.89) | 0.12 (-0.13, 0.42) | 0.0083 (8.64) |
| May | 0.40 (0.25, 0.64) | 0.0088 (5.76) | 0.20 (-0.01, 0.46) | 0.0086 (7.47) |
| June | 0.40 (0.25, 0.68) | 0.0089 (5.70) | 0.13 (-0.04, 0.36) | 0.0094 (9.27) |
| July | 0.40 (0.27, 0.62) | 0.0090 (5.70) | 0.27 (0.10, 0.49) | 0.0090 (6.90) |
| August | 0.46 (0.33, 0.68) | 0.0090 (4.94) | 0.30 (0.13, 0.53) | 0.0090 (6.47) |
| September | 0.46 (0.31, 0.70) | 0.0096 (5.41) | 0.28 (0.08, 0.59) | 0.0093 (6.80) |
| October | 0.20 (0.25, 0.64) | 0.0093 (5.77) | 0.22 (-0.02, 0.54) | 0.0089 (6.91) |
| November | 0.24 (0.11, 0.42) | 0.0083 (7.38) | 0.27 (0.02, 0.60) | 0.0083 (5.62) |
| December | 0.12 (-0.02, 0.31) | 0.0080 (8.42) | 0.13 (-0.16, 0.54) | 0.0080 (6.31) |

The values in parenthesis in the 2nd and 4th columns indicate the 95% confidence band for the values of d; those reported in columns 3rd and 5th are t-values.