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Research article

Asymmetric impact of COVID-19 induced uncertainty on inbound Chinese tourists in Australia: insights from nonlinear ARDL model

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Abstract: This paper explores the asymmetric impact of COVID related uncertainty measured by the newly formulated index (Discussion about Pandemics Index), conceptualized by Baker et al. (2020) and postulated by Ahir et al. (2018) and Ahir et al. (2020) on Chinese tourist arrivals in Australia over the period 1996Q1 to 2020Q1. It is worthwhile to investigate how the "quarantine economy" is adversely impacting tourism in Australia concerning an important market namely the Chinese market. The paper utilized the novel asymmetric (nonlinear autoregressive distributed lag model) to capture the asymmetric association between tourism and uncertainty. The main upshot of the research points out that economic policy uncertainty weighted by the pandemics asymmetrically impacts tourist arrivals. One per cent rise in uncertainty leads to a decline in tourist arrivals by 10 per cent while one per cent decline in uncertainty leads to a rise in tourist arrivals by 0.22 per cent. The effect of the positive change of the policy uncertainty index is more infusing than the impact of negative change so the asymmetry is confirmed. Further, the Wald test endorse asymmetry behaviour across the variables.

Keywords: discussion about pandemics index; COVID-19; tourist arrivals; income; relative price; exchange rate volatility; time series; NARDL model; Australia; China

JEL Codes: C01, C10, C22, Z3

1. Introduction

Towards the end of 2019, the nations worldwide looked on as the city of Wuhan in China and then the province of Hubei together comprising of around 72 million residents went for “lock-down”. We all were hopeful that the new virus would be controlled effectively which is now familiar by the name of COVID-19. Despite effective measures, the virus began to be contagious to other nations impacting not only the health of people but also the economies. Gradually the mobility of people got constrained. The supply chain of commodities was interrupted due to restrictions in the movement of freight. In Australia, for example, the effect was initially noticed in tourism business houses which dealt with the movement of people. Australia witnessed a sudden downfall in inbound tourists from China. The Australian Bureau of Statistics (ABS, 2016) reported that in the recent decade China and India were the two important emerging markets, Chinese tourist arrivals reached a level of growth of 22 per cent in 2015–2016. However, as the number of coronavirus afflicted cases spread across the Chinese economy, the Australian dollar showed signs of rapid depreciation because China is a major trading partner. Other nations are also facing falling Chinese demand for services such as air travel and tourism. The implications of the COVID-19 have now become serious since it has spread to other nations. The UNWTO has estimated that international tourists’ arrival globally would decline by 20 per cent to 30 per cent in 2020. According to the estimates of the UNWTO, the loss in terms of income generation worldwide would be around 450 billion US dollars expressed in terms of international tourism receipts. Restrictions in air travel coupled with flight cancellations particularly for leisure, education and business purposes are having a significant impact on the Australian economy. Further, the global spread of the virus is hovering uncertainty and severely impacting people’s business confidence. In this paper, we try to explore how Chinese inbound tourism in Australia is impacted by COVID-19 generated uncertainty, explored through the recently developed index related to COVID-19, familiar by the name “Discussion about Pandemics Index (PI)” developed by Ahir et al. (2018) and Ahir et al. (2020). This is the newly generated version of the World economic Uncertainty Index adapted to encapsulate the pandemic impact, Ahir et al. (2018) and Ahir et al. (2020). Australian tourism policymakers need to understand how COVID-19 induced uncertainty will impact Chinese inbound tourism. Such an analysis will provide timely awareness and will help in formulating better tourism management policies for recuperating the tourism growth momentum.

This study contributes to the existing literature by exploring the asymmetric impact of COVID-19 pandemic induced uncertainty explored through the PI index on inbound Chinese tourists to Australia. The impact of asymmetric uncertainty on Chinese inbound tourism is indeed an unexplored area and the study is expected to throw insights particularly in the Australian context which has a large share of Chines tourists. According to Baker et al. (2020) the COVID-19 pandemic will generate huge shock in the global economy and may lead to a rise in uncertainty comparable to the times of the Great Depression. This paper explores the asymmetric impact of COVID related uncertainty measured by the newly formulated index (Discussion about Pandemics Index) conceptualized by Baker et al. (2020 and postulated by Ahir et al. (2020). The present research will make a unique contribution because i) it is exploring the dynamics of COVID-19 induced uncertainty on tourism in an asymmetric framework applying the pioneering method of Shin et al. (2014); ii) it covers a wide range of time-series data from 1996Q to2020Q1; iii) to produce a more comprehensive picture on the responsiveness of tourism to uncertainty, the study has used income, relative prices, exchange rate volatility, globalization, climatic effects as major control variables, using the nonlinear autoregressive distributed lag model of the cointegrating framework and iv) to our knowledge it is the first study to explore the time series dynamics of uncertainty for Chinese tourists in Australia at the backdrop of the global pandemic incorporating the effects of exchange rate volatility in the face of uncertainty, which may have spillover on tourism. By investigating how the newly constructed COVID-19 induced World economic Uncertainty Index formulated by Ahir et al. (2018) and Ahir et al. (2020) impacts tourism demand, the study attempts to capture the pandemic impact unlike the previous which are based on dummy variables. The major explanatory variable as defined by Ahir et al. (2018) and Ahir et al. (2020) is “Discussion about Pandemics Index (PI)” has not been widely used so the paper makes a unique contribution by utilizing the new time series data sets. Further the absence of earlier studies quantifying this impact of economic uncertainty shocks for the Australian economy make the study interesting, particularly because Australia is a major trading partner of China; and the Australian tourism industry already had a tough period with the bush fire and now the COVID-19 restrictions implying that it would not be all that same before the tourism industry recovers. The paper henceforth is designed as follows the subsequent section delves on the recent literature related to uncertainty and tourism, the materials and methods used are explained in Section 3 the major results are discussed in Section 4 and the paper is finally concluded in Section 5.

2. Review of literature

2.1. Tourism and uncertainty

In today’s globalized world the importance of uncertainty is crucial in shaping economic policy decisions. According to Eberly (1994) households generally, postpone decisions to procure non-essential commodities when there is a situation of high chances of uncertainty regarding earnings. The decision of the household to postpone consumption ultimately transmits to a shock in production thereby leading to the fall in GDP; Bloom et al. (2007). The uncertainty induced policy decisions impacts consumer decisions adversely and this ultimately lowers economic growth, (Bloom, 2009; Pastor & Veronesi, 2012). Williams and Balaz (2014) urge that there is a need for stronger theoretical underpinning on the concept of risk and uncertainty related to tourism. The study argues that the impact of uncertainty on tourism may vary across economies and income groups. Policy analysts need to consider wide-ranging behaviour of individual assessment-based travel decisions in the face of uncertainty. Economic Policy Uncertainty has a stronger impact in reducing growth than monetary or fiscal policies, Handley & Limao (2015). Baker et al. (2016) developed an economic policy uncertainty index (EPU) which is increasingly used in the literature to study its impact on the behaviour of firms, households, corporates and trade. The Baker et al. (2016) EPU index encapsulates information about uncertainty from leading dailies, stock markets, business surveys and policies about taxes. The EPU index has generated wide-ranging applications in the literature on tourism demand across varying periods in different countries.

Giglio et al. (2016) observe that the behaviour of the household’s decisions to postpone consumption becomes tougher during the times of economic downswings. Barrero et al. (2017) discuss that the uncertainty has a long-term impact upon the economy. Caggiano et al. (2017) discuss that Economic Policy Uncertainty (EPU) has a more important bearing on unemployment concerning monetary policy shock wave. Gozgor and Ongan (2017) based on cointegration model, using quarterly data over 1998Q1 to 2015Q4 for tourism expenditure in the USA discusses that EPU negatively impacts tourism expenditure in the long-run. Tsui et al. (2017) based on a panel gravity model study the impact of EPU on business tourism in New Zealand. Apart from EPU trade, distance and flight seats were significant factors in explaining the demand for business tourism in New Zealand. Such findings are crucial for policy interventions in expanding tourism for business purpose in New Zealand. Demir and Gözgör (2018) explores the impact of policy-related economic uncertainty on tourism demand. The study concludes based on a panel data set for fifteen countries that high rate of policy-related uncertainty in a country lowers outbound tourism flows. Ongan and Gozgor (2018) using quarterly data sets over 1996Q1 to 2015Q1 explores the impact of EPU on tourist arrivals in the United States from Japan. The paper concludes based on cointegrating models that one per cent variation in the EPU leads to falling in the number of Japanese tourist arrivals in the USA by 4.7 per cent in the long-run. Gozgor and Demir (2018) investigates the effect of economic policy uncertainty on outbound travel expenses for a panel set of seventeen developing and developed countries based on advanced time series techniques. The paper concludes that economic policy uncertainty impacts travel expenses negatively further the impact is stronger for the case of the developing economies. Isik et al. (2019) utilizes monthly data for tourist arrivals over January 1996 to September 2017 in the USA, from the countries of Mexico and Canada to study the impact of EPU. The study finds that Canadian tourists were more sensitive to rising EPU in comparison to the Mexican tourists. The paper concludes that EPU is a significant factor in predicting tourist arrivals. Wu and Wu (2019) studied the impact of EPU on tourism in Ireland, Greece, Portugal and Spain using wavelength techniques based on annual observations, 1995 to 2015. The study concludes that in the short-run there is a one-directional causal association from EPU to tourism receipts and in the long-run, there is both way causality between tourism receipts and EPU. The paper thrusts upon the importance of continued government intervention in these European countries to expand tourism. Demir et al. (2019) using the geopolitical index, analyses the impact on inbound tourism for a set of eighteen countriesfrom1995 to 2016. Using advanced econometric techniques, the study concludes that the geopolitical index adversely impacts tourism. Akadiri et al. (2019) utilizing panel data across countries over the period 1995 to 2016 explored the impact of EPU upon tourist arrivals. Based on the new Granger causality tests, proposed Emirmahmutoglu and Kose (2011), for the heterogeneous panel, Akadiri et al. (2019) concludes that there is two-way causality between tourist arrivals and EPU for France, United States and Ireland, one-directional causality for Canada, China, Brazil and Germany. However, for the countries of Chile, Japan, South Korea no causality was observed. The paper suggests that countries which have bidirectional causality between tourism and EPU needs to explore why EPU is generating a feedback impact on tourism.

Nguyen and Schinckus (2020) point out that in the event of uncertainty people may travel frequently to nearby destinations but may reduce spending in the face of falling incomes. The paper concludes that EPU has a manifold impact on tourism. Khan et al. (2020) based on the gravity model study the impact of EPU on inbound tourism in the United Kingdom. Based on time-varying Granger model the study finds that EPU granger causes tourism in the United Kingdom. The paper observes that policy measures should reflect upon time-varying estimates for accuracy in forecasting tourist arrivals. Sio-Chong and So (2020) explores the adverse impact of the financial crisis, health epidemic and climatic disasters, on inbound tourism in two important cities of China namely Macao and Hong Kong. The paper observes that diverse categories of crisis will adversely impact the tourism industry in varying degrees. Policymakers need to be cautious to be able to tackle the varying impacts of uncertainty upon tourism and ensure that more tourists visit popular destinations during favourable times.

The increasing importance of impact of the uncertainty in today's globalized economy has prompted many scholars to consider it as an additional explanatory factor in analyzing tourism demand along with the well-established explanatory factors in the literature, for example, Gross Domestic Product, Consumer Price Index and exchange rate volatility; Li et al. (2005), Thompson & Thompson (2010), Isik & Radulescu (2017), Ongan et al. (2017), Isik et al. (2018), Isik et al. (2019) and Dogru et al. (2019). Dogru et al. (2019) based on NARDL explored the impact of exchange rate on tourism trade balance with major trading partners of the U.S. The study concludes that exchange rate depreciation of the US improves the trade balance for tourism. Further Isik et al. (2019) explored the impact of exchange rate fluctuations based on the NARDL model for tourism demand in Turkey. The study concludes that depreciation of Euro expands tourism in Turkey.

There is a general agreement in the current literature that EPU has an adversative impact on numerous economic aspects and policy decision making of business houses. A growing number of studies recently discuss that EPU effect on numerous economic factors is often asymmetric. The subject matter of asymmetry in the EPU indeed makes the discussion more complex, for example, Bahmani-Oskooee et al. (2019). The notable works that deal with the asymmetric impact of uncertainty on tourism are Schwartz Z (2007), Shareef & McAleer (2007), Chen and Chiou-Wei (2009), Divino & McAleer, (2010) and Sharma (2019). A significant variety of the literature discusses the impact of pandemics on tourism, Zeng et al. (2005) discussed the impact of the SARS epidemic of 2003 on the tourism industry in China. The study suggests that proper planning and strategic partnerships can ensure proper recovery for the tourism industry because it is characteristic of high elasticity of demand. McAleer et al. (2010) explores the effect of the SARS epidemic and Avian Flu disease on inbound international tourism for Asia. The empirical results show that the impact of the SARS epidemic is more intense in comparison to the impact of the Avian Flu disease. Notable recent studies include works of Yang et al. (2020) and Karabulut et al. (2020) among others. Yang et al. (2020) made a pioneering contribution by applying the dynamic stochastic general equilibrium (DSGE) model to study the impact of the COVID-19 on the tourism industry. The study analyses the severity of the impact of the pandemic on tourism. Karabulut et al. (2020) based on the recently developed index, Discussion about Pandemics Index studied the impact on tourism. The study using the methodology discussed by Ahir et al. (2018) and Ahir et al. (2020) concludes that the impact of pandemic reduces tourist arrivals but this is effective for the low-income nations. Karabulut et al. (2020) study is the only research as of now based on the new data sets apart from this present research.

The major conclusion that emerges from the review of literature is that in today's era of a globalized economy uncertainty in any part of the world transmits into economic decision making on the other side of the globe. It not only affects macro factors but impacts consumers decision making. In the event of uncertainty, the vacation plans of consumers get severely impacted because they can be postponed or abandoned. However, the majority of the discussion on uncertainty and tourism is based on a linear framework, yet the crucial shortcoming of linear time series model according to Anoruo (2011) is variables often exhibit nonlinear properties. The present study tries to overcome the limitation by applying a non-linear model in a time series framework. The two major questions that this study will examine in a nonlinear framework: Are tourists sensitive to pandemic uncertainty? If yes what is the extent of responsiveness?

3. Materials and methods

3.1. The model

The baseline model explaining how Chinese tourist inflows in Australia is impacted by uncertainty is explained in the Equation (1), apart from exploring uncertainty impact, Equation (1) examines the other factors affecting tourists' inflows, using variables that are widely available in the literature.

$$TA_{ijt} = \beta_0 + \beta_1 IC_{it} + \beta_2 P_{ijt} + \beta_3 G_{it} + \beta_4 PI + \beta_5 V_{it} + \beta_5 T_{ijt} + D_t 1 + D_t 2 + \lambda_t + u_{it} \quad (1)$$

Here TA represents tourist arrival from China (country i) to Australia (country j) in proportion to other tourists arriving from North Asian region in time t, IC represents per capita income of the i^{ith} country at time t, P indicates the relative price index between country i and j, G is the index of globalization for country i, PI is the measure of pandemic induced uncertainty at global level, V is the exchange rate volatility measure and T is the measure of the temperature difference between the country of origin and the destination country, D1 (encompassing time 1997Q3 to Q41999) and D2 (encompassing time 2008Q to 2011Q3) are dummy variables representing the Asian crisis and the global financial crisis respectively, λ_t shows the time trend and u_{ij} is the usual error term.

Higher per capita income of the Chinese tourists is expected to augment tourism since it enhances the purchasing power, higher relative price in country j in comparison to the country i implies a rise in expenditure which will adversely impact tourist flows. The literature on tourism economics extensively utilizes the ratio of a consumer price index (CPI) of the country of origin from where tourists are arriving and the destination country's CPI, weighted by the exchange rate to measure the price level faced by the tourists in the destination country, for example, Dritsakis (2004) and Morley (1994). So, following the earlier methods here P denotes the ratio of CPI between China and Australia weighted by the real exchange rate. According to Song et al. (2018) there is a reciprocal association between tourism and globalization. Tourism is an important factor in influencing globalization while the entire process of tourism demand is impacted by the dynamics of globalization. Globalization is expected to favourably impact tourism. Uncertainty will dampen tourism and the number of tourists visiting the destination country will fall. The recent uncertainty initiated by the COVID-19 surrounds almost every aspect of living. The containment of the pandemic depends upon the efficacy of social-distancing, lockdowns and availability of proper vaccines and other associated strategies to combat health disorders. It is difficult to predict whether the short-term policy response of the government will continue to affect uncertainty in consumer spending as the pandemic retrocedes.

Exchange rate volatility is associated with uncertainty and hence it will adversely affect tourist inflows. Several studies, for example, Agiomirgianakis et al. (2014) and Akhtar and Hilton (1984) concludes that exchange rate volatility adversely impacts international trade and travel. Exchange rate volatility indicated by V is calculated by using the standard deviation of the logarithmic value of exchange rate (moving average value) expressed in real terms. The rationale behind the inclusion of T in the model is for examination whether climatic conditions affect tourist's decision to travel. Good weather conditions are important for a holiday at the beach and the cruise.

3.2. Data description

3.2.1. Dependent variable

The dependent variable is TA which shows the number of non-resident Chinese tourists' arrivals to Australia in time t as a proportion of total tourists arriving from North Asia to Australia. The data for tourist arrivals is available from the Australian Bureau of Statistics, monthly from 1996 to 2020. It was calculated based on quarterly frequency to bring consistency with the explanatory variables.

Explanatory variables

Data on Gross Domestic Product (GDP) for China, in the local currency, quarterly observations are obtained from Economic Research Database of Federal Reserve Bank of St. Louis. The World Bank extrapolated population data which was obtained from the World Population Prospects, United Nations (2020), as quarterly estimates. This population data was used to divide GDP for China to obtain per capita income, IC. The Consumer Price Index Data (CPI) for both Australia and China is obtained from Economic Research Database of Federal Reserve Bank of St. Louis, as quarterly observations. The real effective exchange rate for China based on quarterly observations is also obtained from the Economic Research Database of Federal Reserve Bank of St. Louis. The P measure was obtained as the relative of CPI of the two countries weighted by the exchange rate. The index of globalization for China is obtained from Swiss Economic Institute annual observations are converted to quarterly observations. The quarterly observations on COVID-19 induced uncertainty index are obtained from the Economic Policy Uncertainty Data Portal. Our major explanatory variable is the "Discussion about Pandemics Index (PI)" postulated by Ahir et al. (2018) & Ahir et al. (2020)[1]. The index is developed by counting the number of times pandemic-related words are used in the Economist Intelligence Unit Country reports, which are available until the first quarter of 2020. A higher index value indicates a higher discussion about pandemics and hence high global economic uncertainty and contrariwise. The distinct characteristic of this index is that its methodology was restructured on April 4, 2020 and also measures deliberations on the COVID-19 pandemic at global and national levels. Baker et al. (2020) discuss that the newly constructed index quantifies the high rise in the levels of economic uncertainty witnessed across the globe during the first quarter of 2020. Last, the data on temperature from the two capital cities of China and Australia was obtained from tutiempo.net portal. The daily temperature data was converted to quarterly observations for maintaining parity with the other explanatory variables. Table 1 provides the details of the description of the variables and the data source. All observations run from 1996 Q1 to 2020Q1. Since some variables are obtained in monetary units and others in real terms all variables are expressed in relative terms for normalization of the data set of observations. Further Table 2 provides an overview of the summary statistics of the variables utilized in the study. Based on Table 2 the mean of TA is 0.24, the standard deviation is 0.19, the mean of IC is 6719.20 and the standard deviation is 5769.49. All observations are positively skewed except T. The kurtosis of PI is quite high, 11.09.

[1] The Appendix provides a detailed exposition on the new measure *Discussion about Pandemics Index (PI)*

Table 1. Data source and description of variables.

Source	Frequency	Description of Variable	Variable Constructed
Australian Bureau of Statistics	Monthly, converted to quarterly observations	Tourist arrivals from China to Australia as a proportion of total tourists from North Asia to Australia.	TA_{ijt} : Proportion of tourist arrivals to Australia from China in time t.
Economic Research Database of Federal Reserve Bank of St. Louis	Quarterly Observations	Gross Domestic Product (GDP)of China expressed in local currency	IC_{it} : Per capita income Obtained by dividing GDP by population.
United Nations, World Population Prospects	Quarterly Estimates	Population	
Economic Research Database of Federal Reserve Bank of St. Louis	Quarterly Observations, the base year 2015	CPI of China & CPI of Australia	P_{ijt} : relative price index, obtained by dividing CPI of China by CPI of Australia weighted by exchange rate.
Economic Research Database of Federal Reserve Bank of St. Louis	Quarterly Observations, the base year 2015	Exchange Rate for China	V_{it}: Volatility Measure of the exchange rate.
Swiss Economic Institute	Annual Observations converted to quarterly observations	Index for Globalization: China	G_{it} : Globalization Index.
Economic Policy Uncertainty data portal	Quarterly Observations	Discussion about Pandemics Index (PI) conceptualized by Baker et al., (2020 and postulated by Ahir, H, N Bloom, and D Furceri (2018) &(2020).	PI_{it}: COVID-19 generated worldwide uncertainty index.
Data Portal Tutiempo.net	Daily observations converted to quarterly average estimates	The temperature of the two capital cities namely Beijing and Canberra	T_{ijt} : Temperature difference in time t between the country i and country j.

Table 2. Descriptive statistics of the variables.

Variables	Mean	Median	Standard deviation	Maximum	Minimum	Skewness	Kurtosis
TA	0.24	0.19	0.19	0.57	0.01	0.35	1.60
IC	6719.20	4300.36	5769.49	19962.22	457.32	0.76	2.27
P	0.88	0.86	0.08	1.22	0.76	1.86	8.01
G	56.36	61.37	8.95	65.10	38.25	−0.69	1.98
PI	1.64	1	2.23	204.1	0	2.54	11.09
V	0.03	0.02	0.02	0.13	0.002	1.02	3.80
T	15.11	23.08	13.19	31.52	−1.95	-0.01	1.22

Note: Compilation Author.

3.3. Econometric methodology

3.3.1. NARDL model

For our empirical estimation we apply the NARDL, (nonlinear autoregressive distributed lag model) postulated by Shin et al. (2014) to explore the cointegrating relation and asymmetric association across the variables. Several studies relating to economics and finance have discussed the significance of the NARDL methodology; for example, Verheyen (2013) discussed the importance of nonlinearity in export demand based on the NARDL methodology, Bahmani-Oskooee & Nayeri (2018) delve on the significance of non-linear asymmetric methodology while studying the demand for money in Australia; Bahmani-Oskooee & Saha (2019) utilized the nonlinear asymmetric model for assessing the asymmetric impact of policy uncertainty on stock prices, Liu et al. (2019) discuss the asymmetric impact of international policies on national policies and further Nasar et al. (2019) pioneering study discusses the importance of the asymmetric impact of economic growth on income inequality in the United States using the NARDL analysis.

The NARDL model is an expansion of the linear ARDL model, Pesaran and Shin (1998, 2001). The ARDL model is applicable for small samples. Further unlike the VECM the NARDL model does not require the same order of integration of the variables, it could be either I(0) or I(1) but not I(2). The NARDL has some advantages over other nonlinear-model for example, Balke and Fomby (1997), Kapetanios, Shin and Snell (2006); and Krolzig (2013). Though such methods have taken into consideration the issue of nonlinearity in an error correction framework, the use is limited since the long-run cointegration of these models are based on non-stationarity properties which are linear. The NARDL model does away with the problem of endogeneity bias. It also does not have the convergence difficulty in case of a large number of parameters. Due to the distinct advantages of the NARDL model this paper applies the method to explore the asymmetry dynamics.

Based on Shin et al. (2014) Equation (2) expresses the long-run cointegrating regression,

$$y_t = \beta^+ x_t^+ + \beta^- x_t^- + u_t \tag{2}$$

y_t is the dependent variable in this context it is TA . x_t refers to the set of explanatory variables, for example, IC, P, PI, V, G and T. β^+ and β^- are the long run parameters to be estimated. x_t is a vector of K*1 regressors which is defined asymmetrically, in particular, x_t is expressed as $x_t = x_0 + x_t^+ + x_t^-$, x_0 is the initial value

Equations (3) and (4) show the decomposition of the explanatory variables into their positive and negative partial sums respectively based on the NARDL model,

$$x_t^{+} = \sum_{j=1}^{t} \Delta x_j^{+} = \sum_{j=1}^{t} max\,(\Delta x_j^{+}, 0) \quad (3)$$

$$x_t^{-} = \sum_{j=1}^{t} \Delta x_j^{-} = \sum_{j=1}^{t} min\,(\Delta x_j^{-}, 0) \quad (4)$$

Equation (2) can be expanded to model contemporaneously the long- and short-run asymmetries within the NARDL framework. The error correction form of the NARDL model for tourist arrivals is expressed in the Equation (5)

$$\Delta TA_t = \theta + \sum_{k=1}^{m} \theta_{1k}\, \Delta TA_{t-k} + \sum_{k=1}^{m} \theta_{2k}\, \Delta IC_{t-k}^{+} + \sum_{k=1}^{m} \theta_{3k}\, \Delta IC_{t-k}^{-} + \sum_{k=1}^{m} \theta_{4k}\, \Delta P_{t-k}^{+} + \sum_{k=1}^{m} \theta_{5k}\, \Delta P_{t-k}^{-} + \sum_{k=1}^{m} \theta_{6k}\, \Delta G_{t-k}^{+} + \sum_{k=1}^{m} \theta_{7k}\, \Delta G_{t-k}^{-} + \sum_{k=1}^{m} \theta_{8k}\, \Delta T_{t-k}^{+} + \sum_{k=1}^{m} \theta_{9k}\, \Delta T_{t-k}^{-} + \sum_{k=1}^{m} \theta_{10k}\, \Delta PI_{t-k}^{+} + \sum_{k=1}^{m} \theta_{11k}\, \Delta PI_{t-k}^{-} \sum_{k=1}^{m} \theta_{12k}\, \Delta V_{t-k}^{+} + \sum_{k=1}^{m} \theta_{13k}\, \Delta V_{t-k}^{-} + \lambda_1\, TA_{t-1} + \lambda_2\, IC_{t-1}^{+} + \lambda_3\, IC_{t-1}^{-} + \lambda_4\, P_{t-1}^{+} + \lambda_5\, P_{t-1}^{-} + \lambda_6\, G_{t-1}^{+} + \lambda_7\, G_{t-1}^{-} + \lambda_8\, T_{t-1}^{+} + \lambda_9\, T_{t-1}^{-} + \lambda_{10}\, PI_{t-1}^{+} + \lambda_{11}\, PI_{t-1}^{-} + \lambda_{12}\, V_{t-1}^{+} + \lambda_{13}\, V_{t-1}^{-} + + ECT_{t-k} + \psi D1_t + \zeta\, D2_t + \mu_t \quad (5)$$

We estimate Equation (5) to explore the asymmetric association and cointegrating relation across tourist arrivals, income, globalization, uncertainty expressed through PI, prices, the volatility of exchange rate and temperature. ECT is the error correction term the coefficient of which denotes rate of divergence from long-run equilibrium.

Δ is the first difference operator; the coefficients θ_{ik}, I = 1,2……11, are short-run coefficients while the coefficients λ_i I = 1,2…..11 denote the long-run coefficients of the model, ψ & ζ are coefficients of the dummy variable. μ_t is the usual disturbance term.

Following the bounds-test method, Shin et al. (2014), the F-statistic is applied to test the null of the hypothesis of no cointegration implying $\lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = \lambda_5 = \lambda_6 = \lambda_7 = \lambda_8 = \lambda_9 = \lambda_{10} = \lambda_{11} = 0$. Next, the Wald Test is applied to test the short-run and long-run asymmetric behaviour. To evaluate the existence of the long-run non-linearity the null hypothesis of long-run symmetry is tested: $\alpha^{+} = \alpha^{-}$; where $\alpha^{+} = {\lambda_i}^{+}/\lambda_1$ i=2,4,6,8,10 and $\alpha^{-} = {\lambda_j}^{-}/\lambda_1$, j = 3,5,7,11

The existence of short-run symmetry is tested as: $\sum_{k=1}^{m} \theta_{ik} = \sum_{k=1}^{m} \theta_{jk}$, I = 2,4,6, 8, 10 and j-3,5,7,9,11.

4. Results and discussion

4.1. Empirical results

4.1.1. Unit root results

Before using any time series method, it is essential to find out the stationary properties of the observations, otherwise, the results obtained may be spurious, Granger & Newbold (1974). To explore the stationary properties of the time series, the augmented Dickey-Fuller unit root test (ADF test), (1979), the DF-GLS unit root test, Elliot, Rothenberg and Stock (ERS), (1996) and the Phillips-Perron unit root test (PP), Phillips, and Perron (1988) are used here. Table 3 summarizes the unit root test results based on ADF, PP and DF-GLS methods. The findings of Table 3 suggest that the variables are integrated of order I(0) or I(1) since none of the variables is of I(2) we can apply the NARDL model without any indecisiveness.

Table 3. Unit root test: ADF and Phillips Perron (PP) and DF-GLS test.

Variables at Level	ADF test statistic	Results	PP Test statistic	Results	DF-GLS test statistic	Results
TA	−1.07	Non-Stationary	−0.62	Non-Stationary	−1.82	Non -stationary
IC	−2.12	Non-Stationary	−1.71	Non-Stationary	−0.98	Non-stationary
P	−4.01	Non-Stationary	−10.08	Non-Stationary	−2.30	Non-stationary
G	−2.84	Non-Stationary	−1.76	Non-Stationary	−1.21	Non-stationary
PI	−4.96*	Stationary I(0)	−65.22*	Stationary I(0)	−1.11	Non-stationary
V	−3.61**	Stationary I(0)	−23.94*	Stationary I(0)	−2.67	Non-stationary
T	−10.67*	Stationary I(0)	−70.48*	Stationary I(0)	−2.13	Non-stationary
Variables in the First Differenced Form	ADF test statistic	Results	PP Test statistic	Results	DF-GLS test statistic	Results
TA	−18.42*	Stationary I(1)	−144.37*	Stationary (1)	−11.45**	Stationary I(1)
IC	−9.01*	Stationary I(1)	−143.26*	Stationary (1)	−26.17**	Stationary (1)
P	−9.03*	Stationary I(1)	−114.50*	Stationary (1)	−4.49**	Stationary I(1)
G	−5.10*	Stationary I(1)	−125.85*	Stationary (1)	−8.54**	Stationary I(1)
PI	−17.81*	Stationary I(1)	−156.85*	Stationary (1)	−6.87**	Stationary I(1)
V	−8.33*	Stationary I(1)	−64.17*	Stationary (1)	−9.32**	Stationary I(1)
T	−10.99*	Stationary I(1)	−69.70*	Stationary (1)	−17.53**	Stationary I(1)
Critical values	1%	−4.12	1%	−19.13	Critical Values at 5% level of significance −3.05, Lags 4	
	5%	−3.48	5%	−13.40		
	10%	−3.17	10%	−10.77		

Note: (*), (**) and (***) denoted the level of significance of 1 per cent, 5 per cent and 10 per cent respectively.

Zivot and Andrews unit root test with one structural break

The standard unit root test tests like the Augmented Dickey-Fuller or Phillips-Perron and the DF-GLS do not explain the structural breaks in the series, Zivot and Andrews (1992) observe that the results of the conventional unit root test may change if there is an endogenous structural break in the series. Table 4 presents the results of the Zivot-Andrews unit root test. From the results of Table 4 we find that the variables are of order I(0) or I(1). Since none of the variables is of order I(2) we estimate the NARDL model subsequently.

Table 4. Zivot-Andrews test results: break in both intercept and trend.

Variables at level	TB	k	*t*	Inference
TA	2007Q3	2	−3.57	Unit root
IC	1997Q3	2	−1.86	Unit root
P	2007Q3	2	−6.96*	I(0)
G	1997Q4	2	−2.08	Unit root
PI	2007Q3	2	−2.50	Unit root
V	2007Q3	2	−5.40*	I(0)
T	2013Q1	2	−4.66***	I(0)
Variables in their first difference				
TA	2019Q1	2	−8.83*	I(1)
IC	2008Q3	2	−6.98*	I(1)
P	2007Q1	2	−2.07	Unit root
G	1997Q1	2	−11.02*	I(1)
PI	2007Q1	2	−9.34*	I(1)
V	2007Q3	2	−9.98*	I(1)
T	2002Q4	2	−24.27*	I(1)

Note: Critical values: 1%: −5.34 5%: −4.80 10%: −4.58. (*), (**) and (***) denoted the level of significance of 1 per cent, 5 per cent and 10 per cent respectively.

4.1.2. NARDL model: empirical estimation

Since none of the variables is of order I(2) we use the NARDL bounds test methodology for cointegration, to find the long-run relationship. The maximum lag order considered is 2, using Schwarz information criterion, based on the study of Pesaran and Shin (1998). Table 5 reports the bounds test of nonlinear cointegration (F-statistics) and the Table 6 sums the model estimation results. Table 5 explains that there is a long-run cointegrating relation between tourist arrivals, the income of the country of origin, prices, globalization, uncertainty, exchange rate volatility and temperature. The test statistic is 7.67 which is above the upper critical bound.

Before analysing the asymmetric impact (both short-run and long-run) of COVID-19 induced uncertainty expressed through the newly formulated index (Discussion about Pandemics Index) on tourist arrivals alongside the other explanatory variables, we perform a series of diagnostic tests and parameter stability test for the robustness of our analysis, explained in Table 6 (lower panel). The Jarque-Bera (J-B) statistics show the test for normality, the Breusch-Godfrey correlation LM test statistic shows the autocorrelation test and Breusch Pagan-Godfrey (heteroskedasticity) statistic tests the ARCH LM tests. Parameters stability check is needed to check for the robustness of any statistical exploration, therefore Brown et al. (1975) CUSUM or CUSUMSQ parameters stability test is applied here. Figure 1 shows the parameter stability based on the CUSUM and CUSUMQ test. The results demonstrate that there is no violation of the standard assumptions of regression

Table 5. Bounds test for nonlinear Cointegration.

Dependent Variable	F-Statistics	95% Lower Bound	95% Upper Bound	Conclusion
TA	7.67	4.42	6.25	Cointegration

Notes: the critical values are found in Narayan (2005).

Table 6. Nonlinear ARDL estimation results

Dependent variable ΔTA_t			
Short Run Estimation			
Variables	Coefficient	t-Statistic	Prob
Constant	1.61**	4.75	0.00
TA_{t-1}	−0.26**	−3.15	0.002
IC^+_{t-1}	0.07**	2.30	0.02
IC^-_{t-1}	0.03	−1.28	0.21
P^+_{t-1}	−0.07**	−2.50	0.01
P^-_{t-1}	0.08	1.24	0.24
G^+_{t-1}	0.06	0.86	0.09
G^-_{t-1}	0.06	0.28	0.77
PI^+_{t-1}	−0.34*	−3.84	0.00
PI^-_{t-1}	0.02	−0.92	0.07
V^+_{t-1}	−0.03	−2.54	0.22
V^-_{t-1}	0.02	2.97	0.32
T^+_{t-1}	−0.01	−0.02	0.69
T^-_{t-1}	−0.005	−0.02	0.23
$D1^{2007\text{ Q3}}$	−0.003**	−3.21	0.02
$D2^{1997Q3}$	−0.01*	−2.69	0.002
ΔIC^+_t	0.01	0.025	0.24
ΔIC^-_t	−0.05	−0.027	−0.69
ΔP^+_t	−0.02	−1.48	0.14
ΔP^-_t	0.03	0.42	0.67
ΔG^+_t	0.11	0.001	1.84
ΔG^-_t	−0.09	0.07	−1.67
ΔPI^+_t	−0.48	−0.69	0.49
ΔPI^-_t	−0.0079	−0.99	0.32
ΔV^+_t	−0.003	−1.19	0.06
ΔV^-_t	0.001	0.08	0.09
ΔT^+_t	0.05	1.58	0.11
ΔT^-_t	0.008	0.12	0.90
Diagnostics Test			
ECMt-1	−0.63*		
R^2	0.97		
J-B	1.68		0.43
LM(1)	0.002		0.96
LM(2)	0.37		0.54
ARCH(1)	0.004		0.94
ARCH(2)	0.52		0.76

Notes: J-B denotes the Jarque-Bera test statistic for normality, LM(.) is the test for autocorrelation for lag order shown in (.) and ARCH(.) is the test for heteroscedasticity, up to the lag order shown in (.). (*), (**) and (***) denoted the level of significance of 1 per cent, 5 per cent and 10 per cent respectively. (+) and (-) superscripts indicate the positive and negative partial sums respectively (+) and (-) superscripts indicate the positive and negative partial sums respectively.

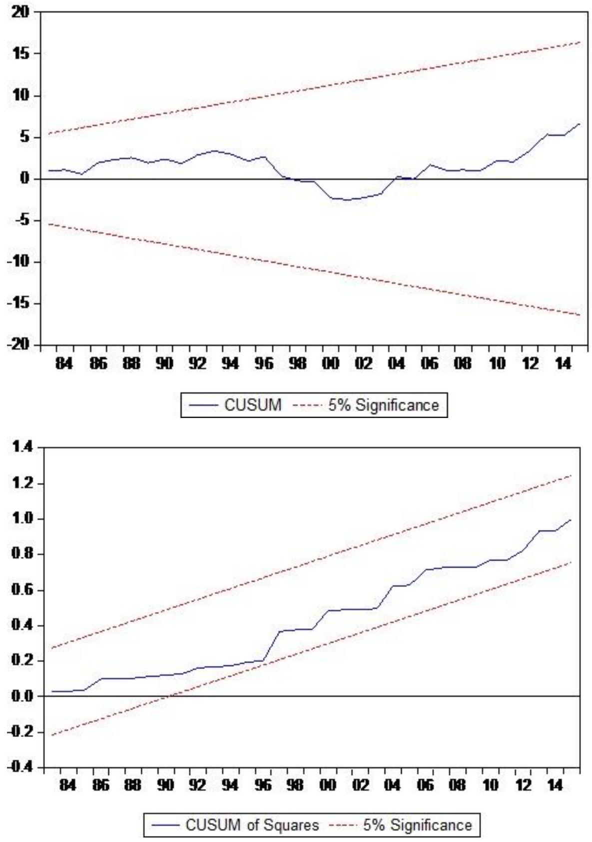

Figure 1. CUSUM and CUSUM(Q) test on parameter stability.

Before proceeding with the findings of our analysis, it would be useful to illustrate the implications of the coefficients based on the asymmetric parameters. For a significant positive coefficient for positive (negative) variations of an explanatory variable imply that when the explanatory variable rises (falls), the dependent variable tends to rise (fall). Again, for a significant negative coefficient for positive (negative) variations of the independent variable imply that when the explanatory variable increases (decreases), the dependent variable tends to fall (rise). Based on the results of Table (6) we find that in the short-run IC impacts positively and significantly upon TA but the negative impact is not significant, again for P the negative impact is not significant. Both for V and PI the asymmetric impact for both positive and negative change is significant in the short-run. One per cent rise in PI leads to a fall in tourist flows by 0.34 per cent again one per cent fall in uncertainty leads to a rise in tourist flows by 0.02 per cent. One per cent rise in exchange rate volatility leads to a fall in tourist flows by 0.03 again one per cent rise in exchange rate volatility leads to a rise in tourist flows by 0.02 per cent.

The results of the long-term parameters are reported in Table 7. The baseline findings Table 7 puts forward that tourist arrivals are being affected by income, price, exchange rate volatility, globalization and COVID-19 uncertainty index namely PI, significantly and asymmetrically. One per cent rise (fall) in income leads to rising (fall) in tourist inflows by 0.067 (0.09) per cent. The largest impact on tourist arrivals come from uncertainty PI. One per cent rise in PI leads to a decline in tourism by 10 per cent while one per cent fall in uncertainty leads to a rise in tourist inflows by 0.22. So, the negative impact is higher than the positive impact implying the existence of asymmetric behaviour. The impact of the rise in per capita income on tourism is different from the impact due to the decline in income so the asymmetry is confirmed. Falling relative prices impact tourism more effectively than the rise in relative prices, verifying the high price elasticity behaviour of tourism. The negative impact on tourism due to one per cent fall in the globalization index is 0.15 per cent while rising globalization index by one per cent raises tourism demand by 0.06 per cent. Such a behaviour confirms the risk-averse nature of the majority of travellers. It is widely acknowledged in the tourism literature that the sector faces high flexibility in demand and is also vulnerable to shocks owing to war, pandemics and political uncertainty. The new globalized order implies that shocks have a whirlpool effect on the major economies and this makes tourism all the more vulnerable during downswings. The Wald test result reported in the lower panel of Table 7 confirm the asymmetric behaviour.[2]

Table 7. Long-run relations.

Dependent variable ΔTA_t		
Variables	Coefficient	P-value
Constant	−1.86**	0.01
IC^+	0.067**	0.00
IC^-	−0. 099*	0.029
P^+	−0.001**	0.024
P^-	0.040*	0.00
G^+	0.06**	0.02
G^-	−0.15**	0.00
PI^+	−0.10*	0.001
PI^-	0.22*	0.002
V^+	−0.02**	0.01
V^-	0.004**	0.03
T^+	−0.12**	0.001
T^-	−0.023*	0.04
Symmetric Estimation		
W_{LRIC}	6.29**	0.007
W_{LRP}	12.17**	0.004
W_{LRG}	19.3**	0.00
W_{LRPI}	4.67**	0.00
W_{LRV}	260.0*	0.00
W_{LRT}	11.28**	0.001

Notes: W_{LRIC} , $W_{LRP}, W_{LRG}, W_{LRV}, W_{LRU}$ *and* W_{LRT} refer to the Wald test for long-run symmetry for the variables IC, P, G, V, PI and T. (*), (**) and (***) denoted the level of significance of 1 per cent, 5 per cent and 10 per cent respectively (+) and (-) superscripts indicate the positive and negative partial sums respectively.

4.2. Discussion

The response of tourist arrivals to uncertainty (COVID-19 induced) and other macro factors diverge subject to the stage of other economic actions. The nonlinear ARDL which takes into

[2] The short-run results for the Wald Test is not provided because they were found to be statistically insignificant implying there is no significant short-run asymmetry impact. Moreover, our focus is on the long-run behaviour.

consideration the asymmetric connections between the variables helps in better understanding of the crucial role of uncertainty (COVID-19 induced) in conjunction to other macro variables in impacting tourist arrivals unlike the analysis based on the linear model. The key results put forward a nonlinear association between the variables. The results are indeed notable for some important reasons as enumerated below. First, we must not ignore that against the background of current economic situation tourist arrivals is not only impacted by COVID-19 induced uncertainty analyzed through the recently constructed index of Ahir et al. (2020) but it is also impacted by the feedback effect of other macro factors. The net effect on tourist arrivals depends on how the new uncertainty index impacts income, prices and exchange rate. With these considerations, a rise in uncertainty induced by the pandemic will not only harm consumers expectations but the consumers will have to function with reduced household incomes. This is the reflection of the deteriorating conditions of production which has major ramifications on tourism. Such findings confirm the works of Chong and Tong et al. (2020), Lanouar, & Goaied (2019), Novelli et al. (2018), Wang, (2009) and Tsai & Chen, (2010).

Social distancing impacts functioning of restaurants, entertainment theatres and shopping malls all of which are significantly interlinked with travel. To be fair, policymakers themselves are confronted with high degrees of uncertainty. There is no precedent for a pandemic of this magnitude in modern times, and imposing public health measures (such as travel bans, border closures, prohibiting public events, and closing down businesses) entails complex trade-offs that are changing over time as contagion evolves. In such a situation a certain degree of policy uncertainty is inevitable.

The economic agents which include firms and households are absolutely in a state of shock because they cannot understand what to expect from the government. Quarantine measures are creating a kind of wait and see approach which is also dampening economic activity. Smith (2006) observes that epidemic occurrences, for example, the SARS in 2003 had led to policies of public health management like quarantine, closures of establishments, which augmented individual's uncertainty about economic policies. Beutels et al. (2009) discuss that in China the impact of SARS was indeed considerable for sectors like hospitality and leisure, international air travel and tourism during the third quarter of the outbreak but it had a substantial long-term impact. Such findings confirm the analysis obtained from the present study.

Complementary macro-economic policy guidelines can help to reinstate confidence levels among travellers and this would facilitate in the revival of tourism demand as the curve of the COVID-19 contagion flattens. Since tourism is dependent upon the state of affairs of other competing economies the adverse consequences of the pandemic are strongly felt. The widespread fall in international travel has percolated into the financial markets. Such behaviour is enhancing the risk aversion nature of consumers which in the long-run lowers the consumer confidence. A downfall in the consumer confidence has a negative feedback impact on economic growth. In comparison to the negative impact of the SARS epidemic, the situation at present is graver because the global chain of integration has expanded. This heightens the negative spill-over impacts. China being a major player as far the contribution in global output is concerned, the adverse shock wave from China is augmenting the risks in trade and travel industry.

In the long-run improvement in household spending behaviour will positively impact tourism however the net impact depends on the rate of new job creation and productivity gains. As of now, uncertainty impact will keep investment opportunities particularly in the tourism sector feeble and this will constrain overall expansion of the economy.

5. Conclusion

This paper explored the impact of COVID-19 pandemic induced uncertainty through the new index “Discussion about Pandemics Index (PI)” conceptualized by Baker et al. (2020) and the methodology developed by Ahir et al. (2018) and Ahir et al. (2020) on international tourist arrivals in Australia from China based on the nonlinear autoregressive distributed lag model postulated by Shin et al. (2014). This is the newly generated version of the World economic Uncertainty Index is adapted to encapsulate the pandemic impact, Ahir et al. (2020) by calculating the per cent of the words related to pandemic episodes in the Economist Intelligence Unit country reports. The period of observations run from 1996 Q1 to 2020Q1. For wide-ranging understanding the importance of major control variables widely used in the tourism literature has been incorporated for example income, relative prices, exchange rate volatility, index of globalization and temperature differences to proxy climatic impact. The major outcome of this study confirms the results of previous studies which have utilized EPU as an explanatory variable to explain the demand for tourism. One per cent rise in uncertainty induced by pandemics expressed through the index PI leads to a decline in tourism by 10 per cent while one per cent decline leads to a rise in tourism by 0.22 per cent. The impact of the positive change of the uncertainty index expressed through PI is more pervading than the impact of the negative change so the asymmetric behaviour is confirmed. The results of the Wald Test confirm the long-run asymmetric association between tourism, income, relative price, uncertainty, exchange rate volatility, globalization and climatic conditions. To encapsulate, the COVID-19 pandemic has generated huge shock waves of uncertainty which may be similar to the level of uncertainty witnessed during the periods of the Great Depression. Our study implies that the shrinkage in tourism demand in the recent times is largely due to the pandemic because it creates “the quarantine economy” that stops mobility, raises public concern on health and keeps people indoors.

Travel agents raise serious questions whether in the short-run local tourism will reopen. The situation is indeed grave because of the method of social-distancing. The period around the end of 2020 predicts downfall of the tourism sector by 60 to70 per cent. However, there may be variations depending on the gradualism of reopening the international borders. The situation of decline may not be so grimed if travel restrictions are gradually lifted in July however if restrictions continue till December then we are indeed facing a tough scenario.

As travelling raises the chances of the susceptibility of infection the travel restrictions are imposed in all countries. The strict government orders have generated fear among consumers which will exacerbate uncertainty in travelling in the long-run. Moreover, from the supply-side perspective, there may dearth of hospitality services over the short to medium period because many tourist employees particularly related to wellness tourism are working in the capacity of temporary health workers. This may raise prices of tourism services. So, one can assume a kind of negative association between health care and tourism. The household utility function is dependent on the total consumption of goods and services of which consumption for health is an important determinant. As health deteriorates there is the substitution effect of expenditure from other consumables. Tourism being highly elastic in demand may be substituted for raising health care benefits. The government of Australia needs to put efforts to boost tourism in the post-crisis period so that the sector sees quick recovery, subsidy for tourists may be generated this will crowd-in investment to tourism ancillary industries. For all-inclusive policy implications, the government needs to put efforts to rebuild the health status of the nation along with subsidizing tourism. Such policy instances will raise the overall welfare of the households because tourism expansion will boost employment which will raise income and hence consumption.

Limitations of the study

The shortcoming of the study is its inability to discuss how intersectoral behaviour may impact the tourism industry. Tourism is linked to several key sectors like agriculture, infrastructure development and ancillary services like the travel and hotel sector, perhaps the impact of interlinkages will throw greater understanding on how uncertainty due to pandemic effects tourism. Owing to the paucity of data such investigation could not be generated. The study has not delved into the role of entrepreneurship in tourism to revive confidence among travellers owing to lack of dense time-series data. However, this indeed leaves further scope for research. In sum, a broad socioeconomic policy planning is required to include related sectors of tourism so that business houses can evaluate the role of the risks amidst the pandemic.

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Conflict of interest

The author declares no conflict of interest in this paper.

Data source

All data sets are available in the domain figshare: https://figshare.com/s/003efbd1db90a65ff3bb.

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