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Unveiling the mystery of the responsiveness of inbound tourism to economic policy uncertainty: New evidence from Australia

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Abstract
Using a time-varying parameter vector autoregressive (TVP-VAR) model, this study analyzes how inbound tourist arrivals (TOUR) respond to EPU in Australia. Empirical results show that EPU can Granger cause TOUR in most cases before COVID-19, whereas little evidence supports this finding after the pandemic. At the national level, it is found that EPU was the net risk transmitter before COVID-19 but became the net risk receiver after COVID-19, while TOUR was the net risk receiver over March 2007-March 2020 but became the net risk transmitter in the remaining months. The impulse response functions reflect that a 2.81% decline in the total TOUR was observed due to a 1% increase in EPU, which gradually decayed within 9 months for the sub-sample before COVID-19. Similar findings hold at the state/territory level. These findings provide profound evidence for the national and state/territory governments to allocate tourism resources and formulate supportive tourism policies.

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Keywords
disaggregated analysis, economic policy uncertainty, exchange rate, inbound tourist arrivals, time-varying parameter vector autoregressive model

Introduction

With the gradual reopening of borders and the easing of travel restrictions in the post-pandemic era, there is a renewed global emphasis on the significance of inbound tourism for economic recovery. This emphasis stems from its crucial role in generating foreign exchange earnings, creating job opportunities, and fostering cultural exchange (Lim and Giouvris, 2020; Shi and Li, 2017). Taking Australia as an example, its tourism gross domestic product (GDP) reached $35.1 billion in chain volume terms with international tourism consumption of $6.4 billion, provided 501,400 employment opportunities, and accounted for 1.6% of Australia's economy GDP in 2021-22 financial year (ABS, 2022). Consequently, many countries are dedicating substantial efforts to implementing economic policies to promote inbound tourism. However, it is essential to recognize that the response of inbound tourism to economic policies can vary significantly across different regions due to their unique resource endowments. For instance, Australia, often referred to as an 'island continent', boasts a diverse array of natural, geographical, and cultural landscapes and climates. As a result, it possesses distinctive resource endowments that can be leveraged to develop the tourism industry across its various states/territories[1].

To provide a comprehensive assessment of the destination country's policy-related economic stability, the economic policy uncertainty (EPU) index has been developed, which potentially impacts inbound tourism through two primary mechanisms (Baker et al., 2016): The first mechanism involves exchange rates. It is widely acknowledged that a high EPU index in the destination country can influence market participants' expectations about its economic outlook. This, in turn, can affect the demand and supply of its currency, leading to exchange rate fluctuations and subsequently affecting inbound tourism (Abid, 2020). Second, a high EPU index in the destination country typically signifies an unstable economic environment with high market volatilities, which decreases investor confidence and causes shrinking tourism investments. This, in turn, may lead to inadequate provision of tourism products, services, infrastructure, and facilities in the destination country, ultimately bringing damaging effects on destination image and inbound tourist arrivals (Al-Thaqeb and Algharabali, 2019; Bernanke, 1983).

Unfortunately, existing studies have predominantly focused on the aggregate impact of EPU on inbound tourism, with limited attention given to the interactions between exchange rates and EPU. Addressing this deficiency, this study utilizes evidence from Australia and employs a vector autoregression (VAR) framework to distinguish effects of exchange rates and EPU on inbound tourism at both the national and state/territory levels. In so doing, this study represents three advances over previous studies. First, this study conducts break point tests for inbound tourism to Australia, identifying structural shifts in inbound tourist arrivals at both the national and state/territory levels. This deepens our understanding of how Australia's national and state/territory inbound tourism responds differently to exchange rates and EPU before and after COVID-19 pandemic[2]. Second, a time-varying parameter VAR (TVP-VAR) model with a mixture innovation distribution not only captures the structural breaks resulting from pandemic shocks, but also separately characterizes the dynamic impacts of exchange rates and EPU on inbound tourism. Third, the constructed risk spillover indicators and impulse response functions enable us to explore how risks transmit between

EPU and inbound tourism and identify the state/territory with the highest sensitivity of inbound demand to EPU, thereby offering insights into regional vulnerabilities.

The rest of this study is organized as follows: Literature review section reviews how EPU has been previously researched in existing literature and identifies research gaps. Methodology section introduces the dataset and methodology employed in this study. Empirical results and discussions section presents the empirical results, accompanied by detailed discussions. The final section concludes this study by summarizing the main findings, highlighting their implications, and suggesting avenues for future research.

Literature review

Since the EPU index was developed based on newspaper coverage frequencies of policy, market, and economic indicators to measure the overall stability of an economy, considerable efforts have been made to investigate its impact on tourism demand from different perspectives (Baker et al., 2016; Zhang et al., 2022). Firstly, it is widely supported that EPU negatively influences tourism demand in terms of various indicators for tourism performance. For example, Ongan and Gozgor (2018) employ the unit root and cointegration tests with consideration of unknown structural breaks and find that an increase in the EPU index for Japan significantly decreases its tourists' departures to the United States (US). After controlling world industrial production, Hailemariam and Ivanovski (2022) use a structural VAR (SVAR) model and document that a rising global EPU significantly reduces the demand for US tourism net export expenditures. With the help of a long-run causality modelling approach with a Fourier approximation, Payne et al. (2022) detect the unidirectional causality running from EPU to international tourist arrivals to the Croatian Adriatic coast and confirm negative and significant impacts in the respective coastal counties. Similarly, EPU's negative impacts on tourism demand also apply to other tourism performance indicators such as tourism related companies' stock returns (Ersan et al., 2019), investment policies in hospitality companies (Akron et al., 2020), overseas air travel (Payne and Apergis, 2022), hotel room demand and operating performance (Chen et al., 2020; Madanoglu and Ozdemir, 2019), and domestic tourism spending (Gozgor and Ongan, 2017).

Secondly, profound evidence from different countries and regions also supports the adverse impacts of EPU on tourism demand. In the case of the Organization for Economic Co-operation and Development (OECD) countries, Balli et al. (2018) conduct a wavelet analysis and argue that tourist inflows to destination countries are negatively related to the local EPUs apart from the global EPU. Kuok et al. (2022) use China as a case of developing economies and conclude that China's inbound and outbound tourism demand is negatively affected by its EPU shock based on empirical results of a global VAR approach. Evidence from African countries' tourist arrivals from the major economies also indicates that a positive change in EPUs for Canada, Russia, Spain and the United Kingdom (UK) negatively affects their tourist departures to African countries (Gholipour et al., 2022). Similar findings can also be confirmed in other economies such as Japan (Ongan and Gozgor, 2018), Asian and Pacific Rim countries (Tsui et al., 2018), France, Greece, and the US (Ghosh, 2019), 12 countries in three regions of America, Europe, and Asia-Pacific (Akadiri et al., 2020), the US (Hailemariam and Ivanovski, 2022), Turkey (Irani et al., 2022), and Croatian and European economies (Payne et al., 2022).

Thirdly, however, there is no consensus on the above negative impact of EPU on tourism demand when considering heterogeneity issues in terms of influential periods, income levels, shock types, and levels of tourism demand. For example, Singh et al. (2019) argue that the relationship between EPU and tourist footfalls depends on time dimensions. Using a wavelet analysis, they find that EPU demonstrates a little immediate impact on international tourist footfalls in the US, while the impacts are persistent in the medium and long run. According to Nguyen et al. (2020), heterogenous effects of EPU on domestic and outbound tourism depends on income levels. That is, negative impacts are observed in higher-income economies, but positive impacts are observed in lower- and middle-income economies. Sharma (2021) adopts a nonlinear autoregressive distributed lag model to test how tourism demand responds differently to negative and positive changes in EPU. Based on the evidence from India over the period January 2006–April 2018, the author observes that negative effects caused by increasing EPUs are more penetrating than positive effects caused by decreasing EPUs. To differentiate between tourism peak season and off-season, Jiang et al. (2022) employ a quantile-on-quantile method and focus on the upper and lower quantiles of stock returns of Chinese tourism-listed companies. They observe both negative and positive impacts of the Chinese categorical EPU on stock returns at different distribution levels, and further confirm that during tourism off-season the asymmetry is more obvious at lower and upper quantiles. Inconsistent results regarding how EPU affects tourism demand are also found in Wu and Wu (2019) by reporting a unidirectional causality from European EPU to international tourism receipts in the short run and a bidirectional causality between them in the long run, Chen et al. (2020) by distinguishing between the trough and peak periods in tourists' hotel room demands, Akadiri et al. (2020) by detecting different types of causality among 12 countries in a heterogeneous panel, and so on.

Lastly, despite the above fruitful achievements on the relationship between EPU and tourism demand, few studies except for Payne et al. (2022) and Zhang et al. (2022) have explicitly been conducted from the disaggregated and dynamic perspectives. More specifically, Payne et al. (2022) conduct a disaggregated analysis to compare the differential impacts of Croatian and European EPUs on international tourist arrivals to the Croatian Adriatic coast. They confirm a significant and negative causality running from EPU to international tourist arrivals across the respective coastal counties. Using a TVP-VAR model to capture the time-varying impacts of EPU on Chinese inbound tourism, Zhang et al. (2022) examine how impacts change directions and how impacts gradually weaken as the lag period increases. To enrich the existing literature on the impact of EPU on tourism demand, this study carries out a disaggregated analysis to examine the viewpoint that inbound tourism to Australia's states/territories may respond differently to EPU due to the state/territory disparities in tourism resource endowments and inbound tourism's economic contributions. Further to Zhang et al. (2022), this study constructs risk spillover indicators after estimating a TVP-VAR model with a mixture innovation distribution to explore how risks transmit between EPU and inbound tourism to Australia's states/territories. Findings of this study provide profound evidence for the national and state/territory governments to allocate tourism resources and formulate supportive tourism policies.

Methodology

Variables and data sources

This study aims to adopt a TVP-VAR model with a mixture innovation distribution to differentiate between the time-varying impacts of exchange rates and EPU on inbound tourism to Australia's states/territories. To achieve this, a tri-variate monthly dataset consisting of inbound tourist arrivals to Australia (TOUR), the EPU index for Australia, and the real exchange rate of Australia (REER) over the period January 1998–August 2022 is used in this study, yielding 296 observations. It is noteworthy that the seasonally adjusted number of short-term visitor arrivals to Australia collected from Australian Bureau of Statistics[3] is used to represent TOUR. Moreover, the dataset includes

Australia's total inbound tourist arrivals (TOTAL) as well as its state/territory inbound tourist arrivals to NSW, VIC, QLD, WA, SA, NT, ACT and TAS, but it excludes inbound tourist arrivals to other territories due to its poor data availability and/or extremely low numbers. The monthly EPU data for Australia are sourced from the EPU website (https://www.policyuncertainty.com/index.html). The real broad effective exchange rate for Australia (index 2010 = 100) collected from Federal Reserve Economic Data[4] is used to represent the variable REER. By taking the first-order difference of the logarithmic variable y, its growth rate in month t can be calculated as $\Delta \ln y_t = 100 \times (\ln y_t - \ln y_{t-1})$. For the sake of simplicity, TOUR, EPU, and REER used in empirical modelling represent growth rates of the aforementioned three variables, respectively.

TVP-VAR model

The proposed TVP-VAR model enables us to advance our knowledge about the impact of EPU on the state/territory inbound tourism to Australia from a dynamic perspective, which demonstrates advantages in the following three aspects (Koop et al., 2009; Zhang et al., 2022): First, compared with a traditional VAR model, the estimated time-varying parameters of the TVP-VAR model can timely visualize the impulse response of inbound tourism to EPU at each time point to provide real-time evidence for tourism policymaking in Australia. This visual depiction is especially valuable for distinguishing risk transmission dynamics before and after the COVID-19 pandemic. Second, the TVP-VAR model can effectively eliminate endogeneity by treating TOUR, EPU and REER as endogenous variables and each variable has an equation showing how it evolves over time. For example, TOUR can be modelled as an equation including the lagged values of TOUR itself, EPU and REER, and an error term. This allows us to reliably isolate the time-varying impact of EPU on inbound tourism after controlling exchange rate which has been identified as the most common determinant of inbound tourism in the existing literature. Moreover, this model offers great flexibility in incorporating additional control variables, such as tourists' income and relative prices. Third, the TVP-VAR model uses a mixture innovation distribution, which effectively captures structural breaks caused by few large exogenous shocks (e.g. the COVID-19 pandemic).

As a result, we refer to Koop et al. (2009) and consider the following tri-variate TVP-VAR model with a mixture innovation distribution in this study.

$$y_t = B_{0,t} + \sum_{l=1}^{L} B_{l,t} y_{t-l} + \varepsilon_t, \varepsilon_t \sim \mathrm{N}\left(0_{p\times 1}, H_t\right) \tag{1}$$

where $y_t = (EPU_t, REER, TOUR_t)'$ is a $p \times 1$ vector of observed endogenous variables with $p = 3$ in this study. $B_{0,t}$ is a $p \times 1$ vector of time-varying intercepts, and $B_{l,t}$ $(l = 1, \cdots, L)$ are $p \times p$ matrices of time-varying autoregressive coefficients with lag l. The error term ε_t are independent normal unobserved shocks with zero mean and variance covariance matrix H_t, which is measured by a triangular reduction in equation (2).

$$H_t = A_t^{-1} \Sigma_t \Sigma_t' \left(A_t^{-1}\right)' \tag{2}$$

where Σ_t is a diagonal matrix with diagonal elements $\sigma_{j,t}, j = 1, \cdots, p$, and A_t is the lower triangular matrix $A_t = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ a_{21,t} & 1 & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots \\ a_{p1,t} & a_{p2,t} & \cdots & 1 \end{bmatrix}$.

The time-varying parameters $B_{0,t}, B_{1,t}, \cdots, B_{0p,t}$ are then stacked by columns into an $m \times 1$ vector α_t, $m = p + p^2 L$ and is described as a dynamic process as follows:

$$\alpha_t = \alpha_{t-1} + K_t^{(1)} \eta_t, \eta_t \sim \mathrm{N}(0_{m\times 1}, Q_t) \tag{3}$$

where η_t are independent normal random $m \times 1$ vectors with zero mean and variance covariance matrix Q_t. $K_t^{(1)}$ denotes a scalar with value 0 or 1 to control for structural breaks in the coefficients of the TVP-VAR model. Similarly, the stochastic volatility of the model also allows for structural breaks:

$$h_t = h_{t-1} + K_t^{(2)} u_t, u_t \sim \mathrm{N}\left(0_{p\times 1}, W\right) a_t = a_{t-1} + K_t^{(3)} \varsigma_t, \varsigma_t \sim \mathrm{N}\left(0_{\left[\frac{p(p-1)}{2}\right]\times 1}, C\right) \tag{4}$$

where $h_t = (h_{1,t}, \cdots, h_{p,t})'$ with $h_{j,t} = ln\, \sigma_{j,t}$ and $j = 1, \cdots, p$. $a_t = (a_{21,t}, a_{31,t}, a_{32,t}, \cdots, a_{p(p-1),t})'$ is a $\frac{p(p-1)}{2}$ vector with stacked non-zero elements in A_t by rows. u_t and ς_t are normal random vectors independent with each other. $K_t^{(2)}$ and $K_t^{(3)}$ indicate either 0 or 1 to control for structural breaks in volatility.

Let $K_t = (K_t^{(1)}, K_t^{(2)}, K_t^{(3)})'$ be the 3×1 vector to control for structural breaks. A Bernoulli distribution such that $Pr(K_t^{(j)} = 1) = \pi_j$ is used, and π_j indicates the probability that a structural break occurs at time t for $j = 1, 2, 3$. This study employs the Bayesian approach described in Supplemental Appendix A of Koop et al. (2009) to estimate the proposed tri-variate TVP-VAR model and confirms the optimal lag $L = 3$ based on the Bayesian information criterion (BIC). It is worthwhile to mention that the sample used in the empirical analysis has been truncated from January 1998–August 2022 to May 2002–August 2022 due to one observation loss for taking the first-order difference, three observations loss for determining the VAR model with optimal lag of three, and 48 observations loss for training coefficients of the TVP-VAR model.

Further analysis based on the TVP-VAR model

After estimating the TVP-VAR model, further analysis can be conducted from the following four perspectives. First, following Dogru et al. (2019), this study detects whether TOUR responds differently to positive ($EPU_t^+ = max(EPU_t, 0)$) and negative EPUs ($EPU_t^- = min(EPU_t, 0)$). The same detection of asymmetry can also be applied to REER. As a result, there is $y_t = (EPU_t^+, EPU_t^-, REER_t^+, REER_t^-, TOUR_t)'$ with $p = 5$ for asymmetric relationship analysis.

Second, the Granger causality test is performed to check whether EPU Granger causes TOUR, which requires to check the zero restrictions in $B_{l,t}$. For example, in equation (1), testing the null hypothesis that EPU does not Granger cause TOUR is equivalent to test $b_{1,t}^{(3,1)} = b_{2,t}^{(3,1)} = b_{3,t}^{(3,1)} = 0$ where $b_{l,t}^{(3,1)}$ denotes the $(3, 1)^{\text{th}}$ element in $B_{l,t}$. If the null hypothesis holds, the test statistic follows a $\chi^2(3)$ distribution. The same causality test can also be applied to REER.

Third, referring to Gabauer and Gupta (2018), the risk spillover indicators can be calculated as the net directional connectedness. To this end, the VAR model should be first transformed to its vector moving average (VMA) representation to obtain the results of the generalized impulse response function and the forecast error variance decomposition. Then, for each variable (i.e. EPU, REER and TOUR), the above results can be used to construct the total directional connectedness (TC) from others and to others and standardize them by 100. As a result, the risk spillover indicator is the difference between the TC to others and the TC from others. More importantly, a variable with a positive risk spillover indicator is identified as a risk transmitter which is driving the network, whereas a negative indicator implies that the variable is a risk receiver which is driven by the network.

In addition, the impulse response functions can be obtained to reflect how EPU affects TOUR at each time point. In particular, the impulse responses are evaluated at $t = 2003:01$ and $t = 2020:03$ to represent the period before and after the COVID-19 pandemic, respectively.

Empirical results and discussions

Preliminary tests and analysis

To get an overall picture of the potential co-movements among EPU, exchange rates and inbound tourism, Figure 1 visualizes the evolutions of original EPU, REER and TOUR over the period January 1998–August 2022. As observed, EPU in Panel (a) fluctuated frequently over time with obvious peaks and troughs. For comparison, nominal exchange rates (FXITWI) based on Australian dollar trade-weighted index were represented by the dashed red line in Panel (b), displaying a similar evolutionary pattern to REER over time. Notably, no clear structural breaks were observed either in EPU or exchange rates. As seen in Panel (c), the total inbound tourist arrivals to Australia demonstrated clear seasonality before the pandemic outbreak in March 2020. However, the dramatically declined arrivals after the pandemic indicated the potential structural breaks in inbound tourism to Australia. Similarly, it can be seen in Figure 2 that Australia's state/territory inbound tourist arrivals also exhibited seasonality and potential structural breaks.

Before estimating the TVP-VAR model, the unit root test should be applied to EPU, REER, and the national and state/territory TOUR to confirm the stationarity of these variables. Meanwhile, to

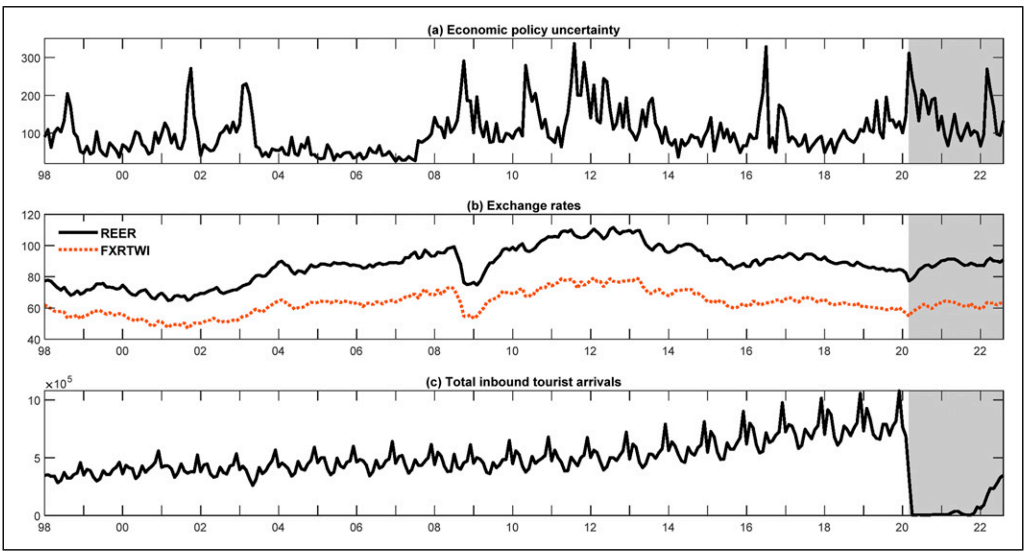

Figure 1. Economic policy uncertainty, exchange rates and original inbound tourist arrivals to Australia. *Notes.* The shaded area indicates the period after the COVID-19 pandemic. In Panel (c), total inbound tourist arrivals are the original data for capturing seasonality which will be adjusted in the empirical analysis.

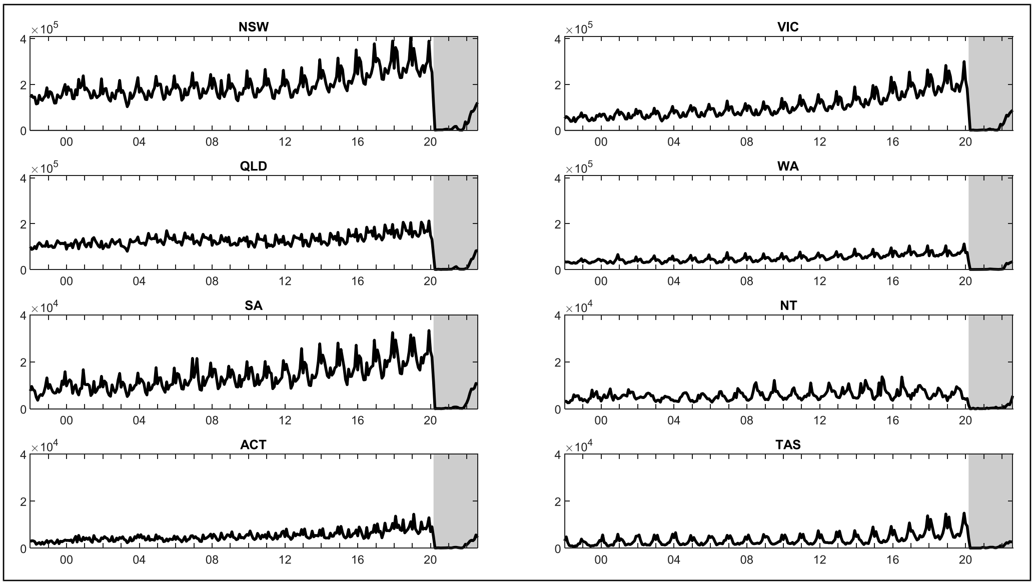

Figure 2. Original inbound tourist arrivals to Australia by state/territory. *Notes*. The shaded area indicates the period after the COVID-19 pandemic. Original arrivals are used to capture seasonality which will be adjusted in the empirical analysis.

detect whether the COVID-19 pandemic causes structural breaks in variables, the break point test is performed. Table 1 reports the results of the unit root and break point tests. As indicated by the ADF (Dickey and Fuller, 1981), PP (Phillips and Perron, 1988) unit root tests and the ZA (Zivot and Andrews, 1992) break point test in Table 1, both EPU and REER are stationary at the 1% level, and there are no structural breaks in these time series. On the contrary, the national and state/territory TOUR are non-stationary, which may be due to structural breaks in TOUR. The ZA test further detects structural breaks in all TOUR series at the 1% level and identifies the COVID-19 pandemic in March 2020 as the break point. This empirically supports that the TVP-VAR model with a mixture innovation distribution is appropriate to capture structural breaks in TOUR which are caused by the large shock of the COVID-19 pandemic (Koop et al., 2009).

Table 2 summarizes the descriptive statistics of EPU, REER and TOUR, providing insights into state/territory disparities in the performance of inbound tourism to Australia. As demonstrated in Table 2, EPU reached a bottom of −166.78% in August 2016 and a peak of 125.20% in November 2016 with the mean of 0.13% and standard deviation of 39.09%, while REER ranged from −24.75% in February 2009 to 27.02% in November 2009 with the mean of 0.49% and standard deviation of 8.51%. According to the results of the Ljung-Box (LB) test, both EPU and REER displayed characteristics of serial autocorrelation over the sample period. Taking into account the detected structural breaks in TOUR, we compare the performance of inbound tourism before and after COVID-19. At the national level, it can be seen that the growth rate of inbound tourist arrivals to Australia (TOUR TOTAL) varied between −30.22% and 26.85% with the mean of 3.45% and standard deviation of 7.17% before COVID-19. However, Australia's inbound tourism was severely disrupted by the pandemic and showed lower mean growth rate and higher volatility after COVID-19. That is, TOUR TOTAL in Table 2 ranged from −574.07% in March 2020 to 399.87% in July 2022 with the mean of −91.53% and the standard deviation of 348.94% after the pandemic.

Table 1. Unit root and break point test results.

	EPU	REER	TOUR								
			TOTAL	NSW	VIC	QLD	WA	SA	NT	ACT	TAS
ADF	−11.63***	−4.37***	−0.73	−1.08	−0.36	−0.26	0.99	−1.10	−1.67	−2.07	−2.18
PP	−23.87***	−3.94***	−2.33	−2.43	−2.41	−2.28	−2.32	−2.42	−2.51	−2.50	−1.69
ZA	−4.19	−4.11	−17.51***	−16.68***	−17.54***	−13.95***	−17.70***	−16.99***	−11.21***	−13.83***	−12.72***
Break point			202003	202003	202003	202003	202003	202003	202003	202003	202003

Notes. EPU, REER and TOUR in this table represent growth rates of EPU, real exchange rates and inbound tourist arrivals. The first two rows show the test statistics of Augmented Dickey-Fuller (ADF) and Pillips-Perron (PP) unit root tests with the null hypothesis that the time series is unit root (non-stationary). The last two rows show the test statistics of Zivot and Andrews (1992) (ZA) break point test and the date of break point with the null hypothesis that the time series has no break points. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 2. Descriptive statistics of variables before and after COVID-19.

			TOUR							
			TOTAL		NSW		VIC		QLD	
	EPU	REER	Before	After	Before	After	Before	After	Before	After
Mean	0.13	0.49	3.45***	−91.53	2.93***	−93.95	6.35***	−91.71	1.82***	−102.40
Std.Dev.	39.09	8.51	7.17	348.94	9.18	336.69	8.28	401.61	8.84	347.44
LB	37.81***	864.05***	234.46***	150.02***	258.85***	140.42***	141.95***	165.51***	164.55***	131.65***
Minimum	−166.78	−24.75	−30.22	−574.07	−44.69	−591.64	−35.58	−679.72	−26.96	−577.97
Date	201608	200902	202001	202003	200108	202003	202001	202007	199801	202007
Maximum	125.20	27.02	26.85	399.87	45.53	442.31	32.68	414.04	29.18	380.00
Date	201611	200911	200404	202207	200008	202207	200404	202207	200404	202207
	WA		SA		NT		ACT		TAS	
	Before	After	Before	After	Before	After	Before	After	Before	After
Mean	3.52***	−103.21*	5.03***	−83.85	1.54	−76.87	5.33***	−72.94	6.44***	−75.98
Std.Dev.	8.84	335.70	14.13	361.02	21.84	326.42	18.40	327.83	22.60	373.33
LB	105.44***	161.12***	145.47***	154.58***	115.27***	124.49***	136.24***	195.48***	95.15***	107.54***
Minimum	−29.22	−552.72	−33.78	−596.36	−80.00	−658.62	−55.17	−493.54	−115.17	−648.31
Date	200008	202003	200105	202007	201605	202003	199807	202006	199806	202003
Maximum	39.18	372.38	61.48	400.16	76.79	299.57	61.01	370.24	83.36	368.89
Date	200011	202207	199905	202207	200805	202201	200008	202207	200009	202105

Notes. LB shows the Ljung-Box test statistics of autocorrelation with 12 lags and the null hypothesis is that there is no autocorrelation. Std.Dev. denotes standard deviation. ***, **, and * denote rejection of the null hypothesis at the 1%, 5%, and 10% significance levels.

For each state/territory in Australia, inbound tourism came to a similar standstill, demonstrating a higher standard deviation, a larger difference between the minimum and maximum, and a sharp decline in the mean growth rate of inbound tourist arrivals after the pandemic. More specifically, before COVID-19, inbound tourism in TAS grew fastest with the highest mean growth rate of 6.44%, followed by VIC (6.35%), ACT (5.33%), SA (5.03%), WA (3.52%), NSW (2.93%), QLD (1.82%), and then NT (1.54%). After COVID-19, ACT performed best with the highest mean (−72.94%), followed by TAS (−75.98%), NT (−76.87%), SA (−83.85%), VIC (−91.71%), NSW (−93.95%), and QLD performed worst with the smallest mean of −102.40%. This reflects that the performance of inbound tourism to Australia exhibited clear state/territory disparities before and after COVID-19. In addition, LB tests for growth rates of the national and state/territory inbound tourist arrivals to Australia indicate the presence of serial autocorrelation at the 1% significance level for all TOUR series.

Results and discussions of the granger causality tests

By restricting our attention to the impact of EPU on inbound tourism after controlling for exchange rates, Table 3 only presents the results of the Granger causality tests with the null hypothesis that EPU does not Granger cause TOUR, while Table A in Supplemental Appendix provides more details about the causal relationships among EPU, REER and TOUR. As seen in Table 3, consistent evidence is found to support that EPU Granger causes the national and state/territory TOUR in the cases of full sample over January 1998–August 2022 and all EPUs before COVID-19. A close inspection of different types of EPUs before COVID-19 indicates that the causality running from EPU to TOUR holds for all positive EPUs and most negative EPUs at the national and state/territory levels. However, this finding is not supported for negative EPUs in the cases of TOTAL, VIC, QLD and NT, showing clear asymmetric and non-causal relationships between EPU and TOUR in these cases. By contrast, little evidence can be found to confirm that EPU Granger causes TOUR after COVID-19 except for the cases of all EPUs and positive EPUs in SA and positive EPUs in ACT. As

Table 3. Results of the Granger causality tests EPU -> TOUR.

	Full sample	Before COVID-19			After COVID-19		
TOUR		All EPUs	Positive EPUs	Negative EPUs	All EPUs	Positive EPUs	Negative EPUs
TOTAL	13.80***	14.25***	16.43***	0.05	1.79	5.86	0.35
NSW	7.75**	8.46**	8.99**	7.84**	3.97	1.9	3.27
VIC	24.54***	25.24***	6.48*	2.9	2.06	1.51	2.67
QLD	9.70**	9.84**	19.32***	1.94	1.13	2.19	0.18
WA	50.59***	51.73***	67.76***	20.25***	4.6	4.84	1.7
SA	8.47**	17.64***	36.78***	12.54***	7.49*	23.60***	1.07
NT	33.56***	38.04***	57.33***	2.58	4.26	5.88	0.51
ACT	91.03***	96.65***	101.66***	36.01***	5.89	6.20*	3.9
TAS	23.97***	25.63***	48.77***	16.41***	2.42	2.05	3.16

Notes. The table shows the Granger causality test statistics with the null hypothesis “EPU->TOUR” meaning that EPU does not Granger cause TOUR. ***, **, and * denote rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively.

a result, it can be argued that the Granger causality running from EPU to TOUR can be frequently observed before COVID-19 and the full sample, which is seldom observed after COVID-19. That is, the COVID-19 has caused a structural break in the causal relationship between EPU and TOUR. Meanwhile, asymmetry is only detected in cases of all EPUs, VIC, QLD, NT before COVID-19, and SA and ACT after COVID-19. These findings are in line with previous studies (Payne et al., 2022; Sharma, 2021) and further confirm clear state/territory disparities in the asymmetric and causal relationships between EPU and inbound tourism to Australia.

Results and discussions of the risk spillover indicators

Figures 3 and 4 visualize how the risk spillover indicators of EPU, REER and TOUR evolve over time at the national and state/territory levels, respectively. At the national level, before COVID-19, positive indicators for EPU imply that EPU was a net risk transmitter which was the main risk source driving the tri-variate TVP-VAR network. REER changed from a net risk receiver driven by the network to a net risk transmitter driving the network in the year 2008–2009. The national TOUR became negative after the year 2007–2008, implying that it changed from a net risk transmitter driving the network to a net risk receiver driven by the network. Interestingly, the risk spillover indicators for TOUR became positive with high volatility after COVID-19. The indicators experienced a sharp increase at the beginning of the pandemic, followed by a dramatic decrease in 2021 and then a gradual increase in 2022. Nevertheless, both EPU and REER displayed an opposite pattern over the period March 2020–August 2022, indicating that they became the net risk receivers driven by the network.

The above findings not only advance our knowledge regarding how risk transmits among EPU, REER and the national TOUR in the tri-variate TVP-VAR network, but also point out the direction of policymaking efforts. As for the time-varying impacts of EPU on TOUR, it can be argued that risk mainly transmitted from EPU to TOUR before COVID-19, suggesting that more efforts should be made to stabilize EPU. This would provide tourism investors and inbound tourists with a stable economic environment and optimistic expectation about Australia's future economy, and then boost

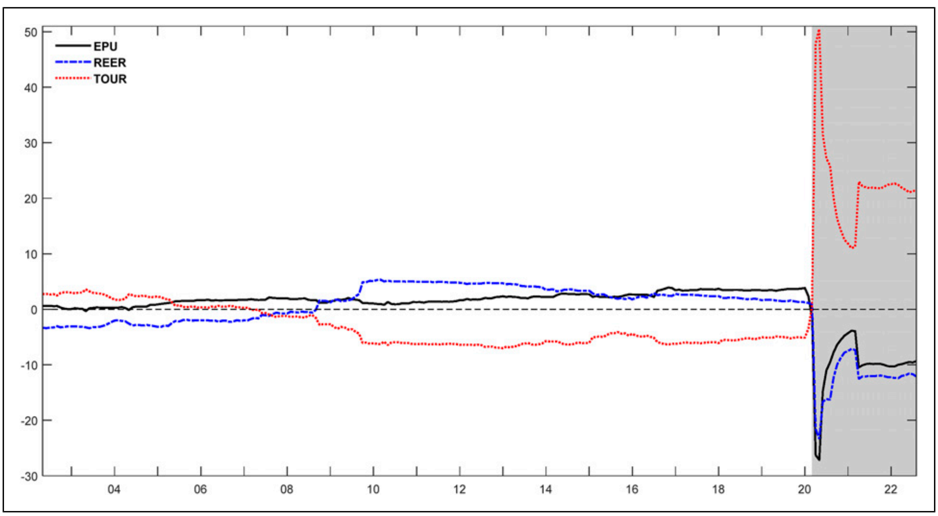

Figure 3. Risk spillover indicators for EPU, REER and TOUR at the national level.

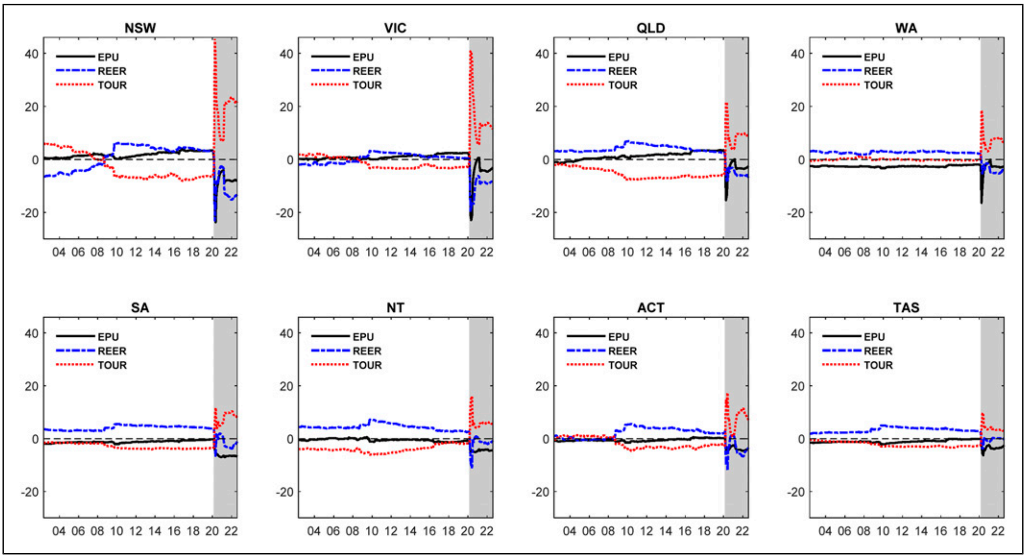

Figure 4. Risk spillover indicators for EPU, REER and TOUR at the state/territory level.

inbound tourism to Australia. On the contrary, risk transmitted mainly from TOUR to EPU and REER after COVID-19, indicating that policies and measures for boosting inbound tourism would also help to stabilize Australia's economic environment.

At the state/territory level, the pattern of risk transmission in the tri-variate TVP-VAR network exhibits clear disparities and structural breaks. Broadly speaking, before COVID-19, positive risk spillover indicators of EPU were frequently observed in NSW, VIC and QLD, negative indicators often appeared in WA, SA and TAS, and indicators in NT and ACT were close to zero. This reflects that EPU was frequently identified as a net risk transmitter driving the network in NSW, VIC and QLD before the pandemic, whereas it became a net risk receiver driven by the network in SA, WA and TAS. No clear evidence differentiated between its role as a net risk transmitter and a net risk receiver in NT and ACT. As for TOUR before COVID-19, its risk spillover indicators became negative after the year 2007–2008 in NSW, VIC and ACT, implying that TOUR changed from a net risk transmitter driving the network to a net risk receiver driven by the network. Negative indicators of TOUR before the pandemic in QLD, SA, NT and TAS supported its role as a net risk receiver, whereas they were quite close to zero in WA. Interestingly, after COVID-19, positive risk spillover indicators of TOUR and negative risk spillover indicators of EPU were observed in all states/territories, reflecting that risk mainly transmitted from TOUR to EPU and REER. To focus on the time-varying impact of EPU on TOUR, a detailed analysis of the risk spillover indicators of REER is not provided here but it can be found in Figure 4.

These findings confirm the presence of state/territory disparities in risk transmission patterns among EPU, REER and TOUR in the tri-variate TVP-VAR network. As observed, NSW and VIC experienced highest increases in their risk transmission indicators after the pandemic outbreak, followed by QLD, WA, NT, ACT and then SA and TAS. That is, inbound tourism in NSW and VIC displayed higher sensitivities to risks after the pandemic outbreak, requiring more attention from national tourism policymaking. For each state/territory, it is suggested that endeavor should be made to boost inbound tourism by allocating more economic resources to the tourism sector and formulating more supportive tourism policies, which helps to stabilize EPU and REER.

Results and discussions of the impulse responses

Apart from the aforementioned net risk transmission among variables, Figure 5[5] presents the impulse response of national TOUR (EPU) to a change in EPU (national TOUR) within 24-month lagged periods. To illustrate the time-varying interactions between EPU and national TOUR, January 2003 and March 2020 are used to represent the periods of before and after COVID-19, respectively. As shown in Figure 5, before COVID-19, a 1% increase in EPU caused an immediate 2.81% decrease in TOUR in the following month, and the impact gradually weakened within 9 months. However, TOUR had no significant response to a change in EPU after COVID-19. Regarding EPU's response to a shock to TOUR before COVID-19, it is observed that a 1% increase in TOUR resulted in a 2-month lagged decrease of 1.92% in EPU, and the impact is persistently significant during the following 3–4 months. After COVID-19, a 2-month lagged decrease of 3.32% in EPU was caused by a 1% increase in TOUR, which became insignificant after 6–7 months.

The above results indicate that national inbound tourism before COVID-19 was negatively affected by a positive EPU shock after controlling for exchange rates, but it became insensitive to an increase in EPU after COVID-19. On the other hand, EPU negatively responded to a positive shock to TOUR with a 2-month lagged impact in both periods. A stronger response with a long decaying period was observed after COVID-19.

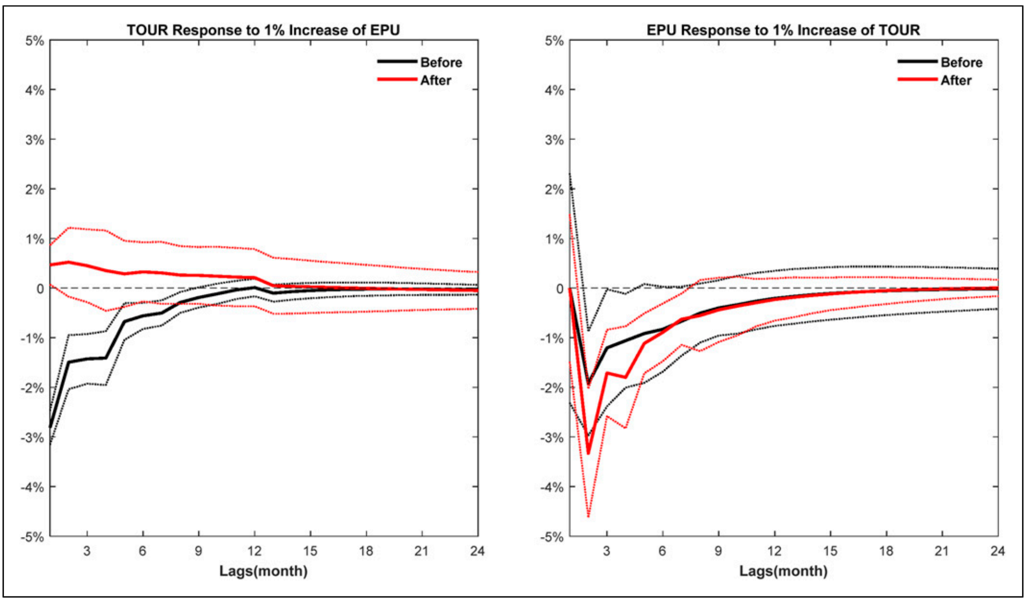

Figure 5. Impulse response functions of EPU and TOUR at the national level. *Notes*. The figure shows the impulse response functions between EPU and national TOUR with lags from 1 to 24 months. The black and red solid lines represent the impulse response before and after the COVID-19 pandemic, respectively. The dotted lines are the corresponding 95% confidence levels by bootstrapping.

At the state/territory level, it can be clearly seen from Figure 6 that TOUR responses differently to an increase in EPU in different states/territories. Before COVID-19, all states/territories experienced an immediate decline in TOUR in response to a 1% increase in EPU, and the impact gradually decayed. Moreover, the decline in NSW, VIC, QLD and WA was larger and longer than that in SA, ACT and TAS. After COVID-19, TOUR in all states/territories demonstrated an insignificant

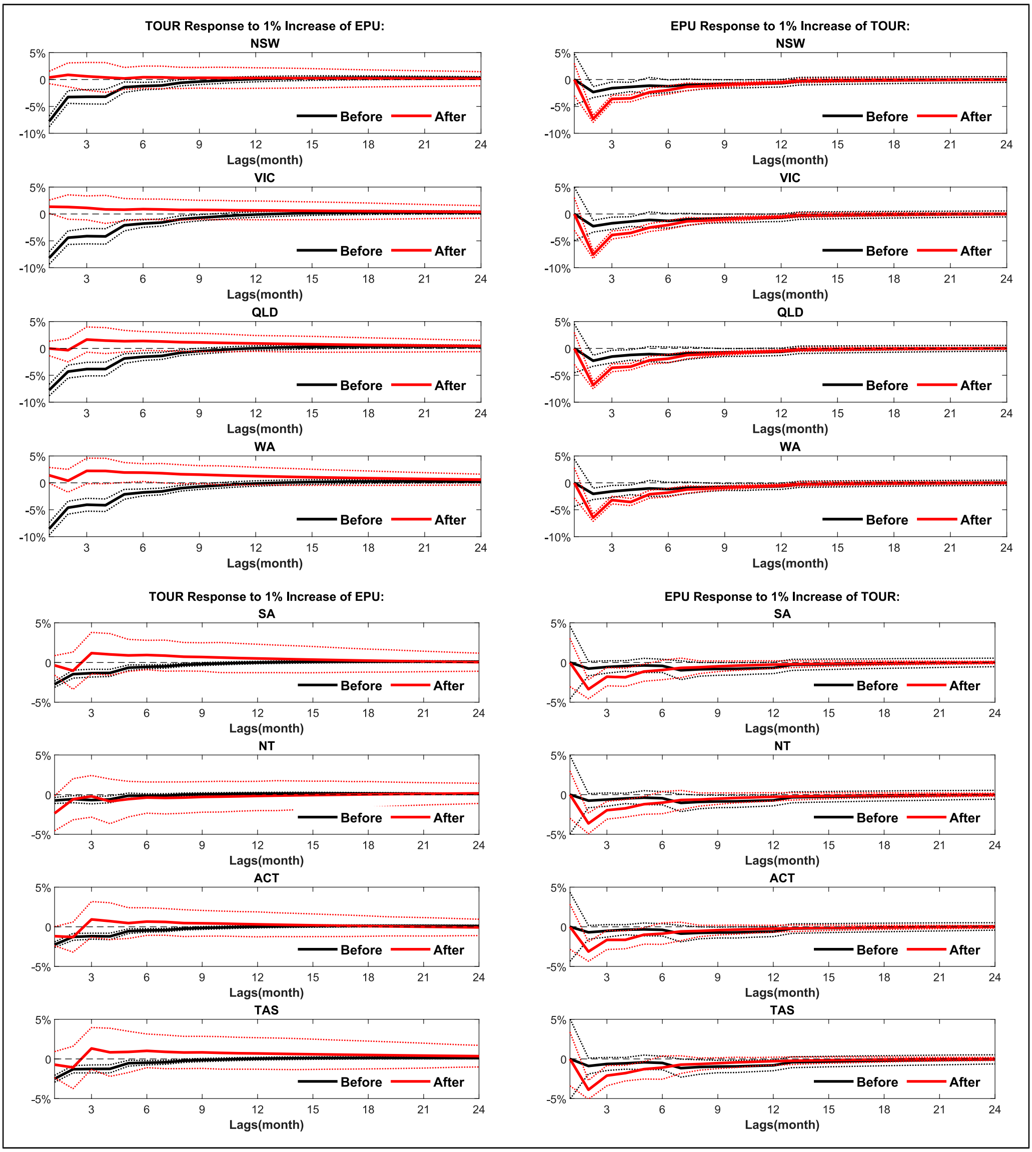

Figure 6. Impulse response functions of EPU and TOUR at the state/territory level. *Notes*. The figure shows the impulse response functions between EPU and state/territory TOUR with lags from 1 to 24 months. The black and red solid lines represent the impulse response before and after the COVID-19 pandemic, respectively. The dotted lines are the corresponding 95% confidence levels by bootstrapping.

response to a change in EPU. On the other hand, state/territory disparities in responsiveness of EPU to TOUR also existed before COVID-19. As observed, a 1% increase in TOUR caused a significant and 2-month lagged decline in EPU in NSW, VIC, QLD and WA, whereas the impacts in SA, NT, ACT and TAS were insignificant. After COVID-19, the negative 2-month lagged responses of EPU to TOUR were stronger and longer in NSW, VIC, QLD and WA than that in SA, NT, ACT and TAS, demonstrating clear state/territory disparities. Overall, all states/territories witnessed a larger decline in EPU after COVID-19. A similar analysis can be conducted to examine how TOUR and REER interact before and after the pandemic, and the results are available on request.

These findings provide us with the following implications: First, state/territory disparities in interactions between inbound tourism and EPU are confirmed in both periods of before and after COVID-19. Second, the observed declines in TOUR caused by an increase in EPU are stronger and longer in NSW, VIC, QLD and WA, indicating that inbound tourism in these states is more sensitive to EPU. This observation can be attributed to the substantial shares of these states' tourism industries in Australia's total tourism industry (STSA, 2022). In the year 2021-2022, the direct tourism output shares were 25.7% in NSW, 20.5% in VIC, 28.4% in QLD, and 11.4% in WA, while their tourism consumption shares were 26%, 21.1%, 27.6% and 11.6%, respectively. In comparison, the direct tourism output shares were 6.2% in SA, 3.5% in TAS, 2.4% in NT, and 1.9% in ACT, with corresponding tourism consumption shares of 6.4% in SA, 3.5% in TAS, 2.2% in NT, and 1.8% in ACT. Accordingly, an unstable economic environment could cause more severe disruptions in tourism-related industries (e.g., hospitality, accommodation, entertainment, and transportation) in NSW, VIC, QLD and WA, thereby bringing greater damage to the overall tourism industry. Moreover, an increase in EPU could significantly reduce investment in tourism infrastructure and services in NSW, VIC, QLD and WA, leading to negative perceptions among inbound tourists and further damaging the tourism industry as a whole. It is suggested that more tourism resources and supportive tourism policies should be directed to these states, especially when the economic environment is unstable. Third, the responsiveness of EPU to TOUR in NSW, VIC, QLD and WA implies that inbound tourism in these states plays a more important role in stabilizing economic environment. Efforts for promoting inbound tourism in these states can also help create a more stable environment for developing economies especially after the pandemic.

Robustness check

To examine the robustness of the main findings concerning the interactions between EPU and exchange rates, this study incorporates inbound tourists' income as a control variable into the proposed TVP-VAR model. This variable is widely recognized as another crucial determinant of

Table 4. Results of the Granger causality tests EPU -> TOUR: GDP as a control variable.

TOUR	Full sample	Before COVID-19			After COVID-19		
		All EPUs	Positive EPUs	Negative EPUs	All EPUs	Positive EPUs	Negative EPUs
TOTAL	8.29**	15.69***	17.22***	2.49	1.21	1.45	0.70
NSW	13.82***	15.86***	6.72*	3.27	0.22	0.68	0.43
VIC	12.08***	13.32***	28.59***	3.04	0.62	1.16	0.17
QLD	38.64***	40.08***	58.14***	5.81	3.77	4.89	1.78
WA	86.15***	87.04***	92.10***	6.83*	1.66	1.79	1.06
SA	7.72**	16.80***	36.02***	14.49***	0.77	1.08	0.71
NT	72.75***	80.73***	95.84***	4.05	3.25	4.05	0.77
ACT	70.57***	73.35***	86.93***	35.16***	5.27	6.02	2.54
TAS	12.45***	13.04***	8.03**	13.17***	0.97	0.76	1.54

Notes. The table shows the Granger causality test statistics with the null hypothesis "EPU->TOUR" meaning that EPU does not Granger cause TOUR controlled for the impact of the income. ***, **, and * denote rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively. The highlighted results do not align with those presented in Table 3.

inbound tourism demand besides exchange rates. Moreover, the GDP of other countries can influence Australia's inbound tourism, but the reverse is typically not true. It is noteworthy that the GDP of inbound tourists' country of origin is commonly used as a proxy for their income (Song et al., 2023). However, data availability can be a challenge as world GDP figures excluding

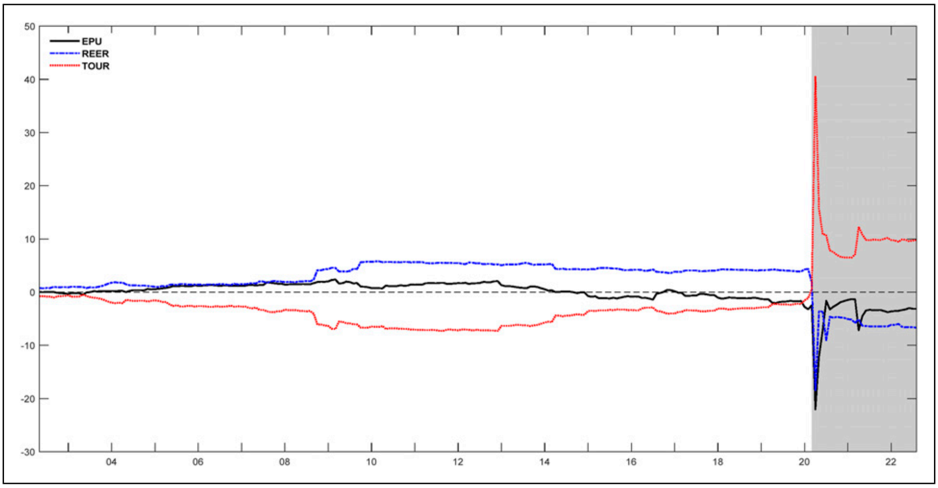

Figure 7. Risk spillover indicators for EPU, REER and TOUR at the national level: GDP as a control variable.

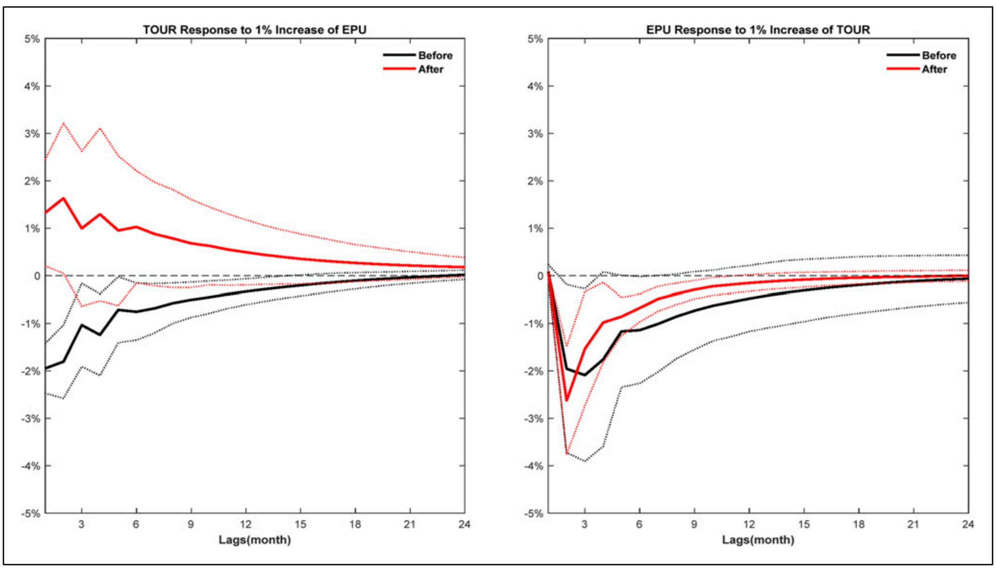

Figure 8. Impulse response functions of EPU and TOUR at the national level: GDP as the control variable.
Notes. The figure shows the impulse response functions between EPU and national TOUR with lags from 1 to 24 months controlled for the impact of the income. The black and red solid lines represent the impulse response before and after the COVID-19 pandemic, respectively. The dotted lines are the corresponding 95% confidence levels by bootstrapping.

Australia are typically released annually. To balance data availability and proxy efficiency, this study focuses on Australia's top 8 inbound tourist source markets, including New Zealand, the USA, the UK, mainland China and Hong Kong, India, Singapore, Japan, and South Korea. These markets collectively contributed to approximately 63.91% of total inbound tourist arrivals to Australia in 2023 (ABS, 2024). Given that these markets are major economies with quarterly GDP data available, this study calculates the GDP growth rate for each quarter over the period from January 1998 to August 2022. Subsequently, this growth rate is evenly distributed across each month within the respective quarter for further analysis.

For simplicity, the robustness analysis results presented here focus on the national level, while the state/territory results can be obtained in a similar way. Comparing the Granger causality test results from EPU to TOUR in Tables 3 and 4, the risk spillover indicators in Figures 3 and 7, and the impulse response plots in Figures 5 and 8, it is evident that the majority of results remain consistent after controlling for inbound tourists' income. Notably, the impulse response analysis in Figure 8 highlights that national inbound tourism before COVID-19 was negatively affected by a positive EPU shock, but to a lesser extent when accounting for the income factor. Consequently, the main findings derived from the proposed TVP-VAR model demonstrate robustness.

Conclusions

Using a TVP-VAR model, this study conducts a disaggregated analysis of how inbound tourism responds to EPU in Australia after controlling for exchange rates. The main findings are as follows: First, it is confirmed that the total inbound tourist arrivals to Australia demonstrated clear seasonality and potential structural breaks, supporting the appropriateness of a TVP-VAR model with a mixture innovation distribution. Second, it is found that the COVID-19 has caused a structural break in the causal relationship between EPU and TOUR, while asymmetry is only detected in cases of TOTAL, VIC, QLD, NT before COVID-19, and SA and ACT after COVID-19, demonstrating state/territory disparities. Third, the national TOUR changed from a net risk transmitter to a net risk receiver after the year 2007–2008, which became positive with high volatility after COVID-19. Meanwhile, it is documented that a positive EPU shock negatively affected national inbound tourism before COVID-19 after controlling for exchange rates, but it became insensitive to an increase in EPU after COVID-19. Finally, empirical evidence supports that clear state/territory disparities and structural breaks exhibit for risk transmission patterns and for responses of inbound tourism to EPU. Particularly, we find that inbound tourism in NSW, VIC, QLD and WA is more sensitive to EPU.

These findings not only advance our knowledge about the relationship between EPU and inbound tourism demand from disaggregated and dynamic perspectives, but also offer valuable empirical insights for national and state/territory tourism policymaking in Australia with consideration of significant breaks caused by the COVID-19 pandemic. Furthermore, the break point tests utilized in this study can serve as a valuable reference for other destinations to identify structural shifts in inbound tourism resulting from both the pandemic and other random shocks such as natural disasters, terrorism incidents, economic crises, transportation disruptions, and geopolitical conflicts. The proposed TVP-VAR model can be flexibly generalized to include additional control variables, such as tourists' income and relative prices, enabling the isolation of the dynamic impacts of exchange rates and EPU on inbound tourism more comprehensively. The risk spillover indicators and impulse response functions constructed in this study can also be used as benchmark risk assessment tools for other destinations, providing a visual representation of how risks transmit between EPU and inbound tourism after controlling exchange rates over time. These insights enhance the ability of worldwide tourism policymakers and industry stakeholders to anticipate and respond effectively to the complex dynamics of inbound tourism within an ever-changing EPU landscape.

Despite these advantages, this study can still be extended in different ways. For example, if monthly data on international tourism consumption in Australia is available, it can be used as an alternative measurement of inbound tourism demand to re-examine how inbound tourism responds to EPU at the state/territory level. Another way is to assess the efficiency and effectiveness of different national and state/territory tourism policies implemented after the pandemic by quantifying their economic and employment consequences.

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Supplemental Material

Supplemental material for this article is available online.

Notes

1. Unique tourism resource endowments can also be found in different states/territories, such as the Great Barrier Reef in Queensland (QLD), the Blue Mountains and Sydney Opera House in New South Wales (NSW), the Twelve Apostles and Californian Redwood Forest in Victoria (VIC), the Hamelin Bay Stingrays and Pinnacles in Western Australia (WA), the Kangaroo Island and Lake Gairdner in South Australia (SA), the Kakadu National Park and Uluru in the Northern Territory (NT), the Parliament House, national galleries and museums in the Australian Capital Territory (ACT), and the Wineglass Bay and Cradle Mountain in Tasmania (TAS).
2. The World Health Organization (WHO) declared a Public Health Emergency of International Concern on 30 January 2020 and characterized the outbreak as a pandemic on 11 March 2020.
3. https://www.abs.gov.au/statistics/industry/tourism-and-transport/overseas-arrivals-and-departures-australia/nov-2022#data-downloads
4. https://fred.stlouisfed.org/
5. To focus on the interactions between EPU and inbound tourism, Figures 5 and 6 do not include impulse response functions of REER and TOUR but they can be available on request.

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