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Does Climate Policy Uncertainty Affect Tourism Demand? Evidence from Time-Varying Causality Tests

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Does Climate Policy Uncertainty Affect Tourism Demand? Evidence from Time-varying Causality Tests

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Abstract

This study examines whether climate policy uncertainty affects the propensity of people to travel. To do so, we employ the Climate Policy Uncertainty (CPU) index and US air travel data to eight regional overseas destinations for the period 2000-2019. Using time-varying causality tests to deal with the structural breaks that exist in the relationship between CPU and US air travel, we find that CPU is a major determinant of air-travel demand to all destinations examined. The results are robust when we control for macroeconomic factors, uncertainty and geopolitical risks. The findings have important implications for destination countries and tourism professionals.

Keywords: Climate policy uncertainty; CPU index; air travel destinations; US; structural breaks; time-varying causality test

JEL codes: C32, C51, L8

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1. INTRODUCTION

Tourism is unambiguously one of the most important drivers of economic growth, accounting for 10.4% of global GDP (WTCC, 2021). Given its importance to the global economy, and tourism destinations in particular, the factors affecting the propensity of people to travel have attracted the interest of the academic community and policy makers. To that end, there is a plethora of studies examining the determinants of tourism demand with a main focus on macroeconomic variables, or proxies of sentiment/uncertainty more recently.[1]

At the same time, tourism is responsible for approximately 8% of global CO_2 emissions; this includes emissions from travelling, leisure, hotels, etc. (Lenzen et al., 2018). Since tourism is such a high emitting industry, but also vulnerable to climate change (Dogru et al., 2019; Scott et al., 2019), national and global policies, aiming to tackle climate change, can have a great impact on tourism demand. This is due to the fact that such policies can increase the cost of travelling (e.g., air tickets), or raise the environmental awareness of people. As such, the latter may change their travelling behaviour by reducing trips in general, or those that require long-haul flights.

Given the increasing interest in climate change and its relevance with tourism activities, the tourism demand literature has substantially incorporated climate change factors (e.g. weather) in the relevant estimations (Liu, 2016). In that framework, tourists are revealing their preferences towards climate through travelling habits. Hence, while the rest of the controls remain constant, the analysis can forecast future trends through projected climatic conditions. Motivated by recent studies utilising news-based indices to investigate the impact of economic policy uncertainty on tourism demand (Dragouni, Filis, Gavriilidis and Santamaria, 2016; Demir and Gozgor, 2018; Apergis and Payne, 2020), this study examines for the first time in the literature the impact of climate policy-induced uncertainty on the propensity of people to travel. To do so, the analysis employs another news-based index, the Climate Policy Uncertainty (CPU) index, recently developed by Gavriilidis (2021), and US air-travel data to eight different overseas regions for the period 2000:1-2019:10. Adopting the approach of time-varying causality tests by Rossi and Wang (2019), the analysis documents that climate policy uncertainty has a major impact on tourism demand across all geographic regions examined. More importantly, the strong evidence of predictability originating from CPU for US air-travel is only obtained under a time-varying approach and not under traditional constant parameter Granger causality tests, which we also perform for the sake of comparison and exhibit weak results. This is due to the fact that the standard Granger predictability framework is mis-specified in the presence of multiple structural breaks in the relationship between CPU and the tourism-related variable (the structural breaks are identified via statistical tests). In addition, the findings remain robust when we control for macroeconomic factors, economic policy uncertainty and geopolitical risks.

The link between climate change and tourism can be theoretically explained by the mechanisms of adaptation and mitigation. In terms of the first definition, adaptation comes as a response to current or expected climatic shocks, while in terms of the latter definition, mitigation comes as a response to climate change and in relevance to the reduction of greenhouse gases (Fussel and Klein, 2005). Therefore, the vulnerability of the tourism industry associated with climate change hazards depends on the industry's capacity to adapt in anticipation of such hazards (Brooks et al., 2005). This capacity is expected to allow the tourism industry to accommodate potential environmental risks (Adger et al., 2005; Linnenluecke and Griffiths, 2010). The

[1] For a detailed review on the determinants of tourism demand please see Song, Dwyer, Li, and Cao (2012) and Song, Qiu and Park (2019).

implementation of adaptation strategies/policies seems to be the only means to deal with climate uncertainties (Hoffmann et al., 2009; Linnenluecke et al., 2011; Linnenluecke and Griffiths, 2012).

The contribution of the paper is twofold. First, it contributes to the literature examining a new determinant of tourism demand. Specifically, it adds to the existing literature by introducing a new variable, the climate policy uncertainty index, and finds that this bears an important effect on tourism demand, yet proper inferences require a time-varying approach to account for regime-changes. So far, prior studies utilising news-based indices have focused on uncertainty induced by economic policy or geopolitical risk. The advantage of using this index is that it focuses on uncertainty solely induced by climate policy, which can be unrelated to other forms of uncertainty, and whose outcomes are particularly relevant to the tourism industry. To that end, the second contribution of the study is that it adds to the growing literature on climate change and climate policies and how these may affect the tourism industry. In fact, this study is timely in view of the recent UN Climate Change Conference (COP26) and the "Glasgow Declaration for Climate Action in Tourism", where businesses and countries committed to reduce emissions related to the tourism industry by half till 2030 and accomplish net zero till 2050.[2]

The rest of the paper is organized as follows. Section 2 discusses the findings of the previous literature, Section 3 presents the data and methodology, while Section 4 discusses the results. Finally, Section 5 concludes the study.

2. LITERATURE REVIEW

The climate footprint of tourism

Tourism may well be considered as a driver of global economic growth, yet this comes at an environmental cost. Over the past decades, there has been a plethora of studies examining the contribution of tourism in greenhouse gas emissions and its climate footprint. For instance, early studies by Becken (2002) and Becken and Simmons (2002) find that overseas tourists add 6% on New Zealand's CO_2 emissions and that tourist activities (e.g., air travel) consume more energy than tourist attractions. In addition, Patterson and McDonald (2004) highlight that amongst twenty five industries in New Zealand, the tourism industry is the second highest emitter. Gössling and Hall (2008) relate the footprint of the tourism industry in Sweden with its contribution to the Swedish economy. Specifically, the authors report that although tourism contributes 11% of national CO_2 emissions, it only contributes 2.8% of Sweden's GDP.

Evidence from other countries about the contribution of tourism in CO_2 emissions yield similar results. For example, Gössling et al. (2010) report that emissions from German tourism account for 4.5% of national emissions. Another study by Gössling (2012) examines the energy use of tourism in fourteen Caribbean countries. The findings indicate that across all countries examined, emissions from tourism account for at least one third of national emissions. Katircioglu (2014) finds that tourism in Turkey, during the period 1960-2010, was a major producer of CO_2 emissions, while Tang et al. (2014), Tsai et al. (2014), and Durbarry and Seetanah (2015) report similar findings for China, Taiwan and Mauritius, respectively. Zaman et al. (2016), by using a sample of thirty four countries, spanning the period 2005-2013, provide evidence of tourism-induced emissions and draw the attention of policy makers for the need to

[2] The Glasgow Declaration is available at: https://www.oneplanetnetwork.org/sites/default/files/2021-11/GlasgowDeclaration_EN_0.pdf

promote more sustainable forms of tourism, while Zhang and Zhang (2021) also highlight the magnitude of tourism-led CO_2 emissions when examining thirty Chinese provinces for the period 2000-2017.

Despite the evidence on the contribution of tourism to the environmental degradation, another view, consistent with the environmental Kuznets curve (EKC) hypothesis, suggests that there is a dynamic relationship between environmental pollution, economic growth and tourism. More specifically, according to Dinda (2004), there is increased environmental degradation at the early stage of a country's economic development; however, after a threshold of economic development environmental quality increases. To that end, Paramati, Alam and Chen (2017), using data from 22 developed and developing economies, find that tourism in general has a positive effect on the economic growth of the sample countries. Nevertheless, the effect of tourism on the environmental degradation is decreasing at a faster rate in developed countries compared to developing countries. Finally, Lee and Brahmasrene (2013), examining a sample of European countries, report a negative effect of tourism on CO_2 emissions. A possible explanation for these findings may be that developed economies put more emphasis on more environmentally friendly forms of tourism; according to certain studies (Scott, 2011; Weaver, 2011) sustainable forms of tourism, such as ecotourism, can alleviate CO_2 emissions.

Climate policy, uncertainty and tourism demand

Policies aiming to tackle climate change and greenhouse gas (GHG) emissions can have a major impact on tourism demand. This is due to the fact that they can affect the cost of energy, hence the cost of most tourism related activities (electricity cost, travel cost, etc). Moreover, by incorporating such policies to their tourism strategies, countries will need to depart from the traditional approach so far of maximizing economic revenues and tourism arrivals, often at the expense of mitigating climate change (Becken et al., 2020). Nevertheless, over the past years, there has been an increasing trend of implementing sustainable practices in national tourism policies (UNWTO, 2019). In addition to the response of national tourism policies to climate-change policies and regulations, the latter can also affect the economic welfare of households (Stolbova, Monasterolo and Battiston, 2018) and people's attitude towards travelling; in fact, Scott and Becken (2010) argue that people might change their travelling habits shifting to more sustainable choices; for instance, tourists may replace holiday destinations requiring long-haul trips with others of closer proximity. An early study by Gössling, Peeters, and Scott (2008) examines how climate policies, at a regional and global scale, could affect tourism demand on developing countries. The authors find that a potential global climate policy (e.g., reducing emissions from the aviation industry) would likely decrease tourist arrivals in some destinations. To that end, the authors argue that destination countries should amend their national tourism strategies in anticipation of such global scale policies.

From the above, one can infer that climate policies can have a major impact on informing national tourism policies and the attitude of people towards travelling. Another strand of the literature examines how uncertainty affects tourism demand. So far, prior research has focused on how uncertainty induced by economic policy or geopolitical risks can affect tourism demand. For example, Dragouni et al. (2016) report spillover effects from economic policy uncertainty (EPU) to US outbound tourism demand, when economic uncertainty is high. Demir and Gozgor (2018), using a sample of fifteen counties, report a negative impact of EPU to outbound tourism demand. Balli, Shahzad and Uddin (2018) employ a sample of eight countries and find that both domestic and global EPUs are important predictors of tourism demand. Tiwari, Das and Dutta (2019) examine the impact of EPU and geopolitical risk (GPR) on tourism demand in India and show that GPR has a negative impact on tourism demand, which is stronger relative to that of economic policy uncertainty. Similarly, Apergis and Payne (2020) report a negative impact of both economic policy uncertainty and geopolitical risk when examining the US outbound demand to several regional destinations. Furthermore, a recent study by Hailemariam and Ivanovski (2021) reports a negative impact of geopolitical risk on US tourism service exports.

Given that climate policies can directly affect the cost of tourism-related activities, as well as people's behaviour towards travelling, studying how climate policy uncertainty policy can affect tourism demand is a topic worthy of investigation. This is especially the case since uncertainty about climate policies' outcomes is much greater compared to uncertainties induced by other policies (Pindyck, 2013).

3. DATA AND METHODOLOGY

Data and Preliminary Analysis

To perform the analysis, we use data on monthly frequency from January 2000 till October 2019. Data on overseas air travel volume of US citizens, are obtained from the U.S. Department of Commerce and the series are seasonally adjusted using the X-11 procedure. Specifically, we examine the total overseas air travel volume (TOT), and the volume of air-traveling to Europe (EUR), Caribbean (CAR), Asia (ASIA), Central America (CAM), South America (SAM), Middle East (MIDE) Oceania (OCE) and Africa (AFR).

As it regards our novel predictor, i.e. the Climate Policy Uncertainty (CPU) index, this is derived by the recent work of Gavriilidis (2021), who follows the newspapers-based approach of measuring uncertainty developed by Baker, Bloom and Davis (2016).[3] Contrary to the existing policy uncertainty indices, Gavriilidis (2021) focuses on climate policy-related articles from eight leading US newspapers.[4] While CPU is the main predictor, as a control variable, we use the first principal component (PC1) derived from a host of other predictors that have been recently suggested by Apergis and Payne (2020), who analyse the role of general economic uncertainty and geopolitical risks on the same set of dependent variables (i.e. overseas air passenger travel of US citizens). Accordingly, we include the common (PC1-based) information content of the broad real effective exchange rate for the US (BREER) and industrial production (INDPR)[5], obtained from the Federal Reserve Bank of St. Louis, the geopolitical risk (GPR) index by Caldara and Iacoviello (2018),[6] and the US (USEPU) and global (GEPU) economic policy uncertainty indices by Baker et al. (2016)[7] and Davis (2016) respectively.[8] Table 1 presents the descriptive statistics of the series. According to these, US outbound air-travelling was mostly to the European, Caribbean and Asian regions, while among the uncertainty metrics, the CPU index is the most volatile.

[3] The CPU index can be downloaded from: http://policyuncertainty.com/climate_uncertainty.html.
[4] For more information about the construction of the index, please refer to Gavriilidis (2021).
[5] When we usage the real personal disposable income per capita or the coincident index instead of the INDPR index in the construction of the PC1 results remain qualitatively similar; the results are available upon request from the authors.
[6] The data can be retrieved from: https://www.matteoiacoviello.com//gpr.htm.
[7] The data is downloadable from: http://policyuncertainty.com/us_monthly.html.
[8] The data can be obtained from: http://policyuncertainty.com/global_monthly.html.

Table 1. Descriptive statistics

Variables	Mean	Std. Dev.	Min	Max
TOT	2,541,048	648,864.8	1,422,363	5,131,219
EUR	1,066,586	380,786.9	414,958	2,566,724
CAM	200,370	64,281.6	73,723	364,499
CAR	518,367	161,880.9	220,141	1,006,030
SAM	167,881	37,327.3	99,264	290,232
AFR	25,886	9,988.9	6,956	61,360
MIDE	101,549	65,222.6	13,434	256,427
ASIA	399,548	82,794.8	176,244	611,415
OCE	60,861	13,956.7	35,157	108,323
GPR	104	70.7	27	545
GEPU	121	51.6	48	307
USEPU	125	48.4	45	284
BREER	110	9.6	93	129
INDPR	100	5.6	87	111
CPU Index	88.72	71.28	1.23	629.03

Note: The table presents the summary statistics of the series employed in the study.

We begin our analysis by exploring our series for the presence of unit roots; to do so, we employ the ADF-GLS test by Elliot et al. (1996). The results are reported in Table 2, according to which the null hypothesis of a unit root across is rejected at all the first-differenced series examined. Hence, we employ first-differenced data in our time-varying causality tests.

Table 2. ADF-GLS test for unit roots

Variables	ADF-GLS test	
	Levels	First differences
TOTOVR	-1.36(4)	-7.54(3)***
EUR	-1.28(5)	-7.13(3)***
CAM	-1.33(4)	-6.58(3)***
CAR	-1.38(5)	-7.19(4)***
SAM	-1.26(5)	-7.81(4)***
AFR	-1.34(3)	-6.42(2)***
MIDE	-1.38(6)	-6.58(4)***
ASIA	-1.16(5)	-8.34(4)***
OCE	-1.42(5)	-6.38(3)***
GPR	-1.31(4)	-6.74(3)***
GEPU	-1.46(5)	-6.26(4)***
USEPU	-1.42(6)	-6.39(5)***
BREER	-1.35(5)	-6.78(4)***
INDPR	-1.30(5)	-7.24(3)***
CPU	-0.47(6)	-6.82(4)***

Note: The optimal number of lags is shown in the parentheses; *** indicates significance at the 1% level.

Methodology

This study adopts the approach by Rossi and Wang (2019) to analyse the time-varying effect of CPU on total and eight regional overseas air passenger travel of US citizens. Due to the presence of structural breaks, which we detect statistically, this approach provides a more reliable inference on predictability compared to a constant-parameter Granger causality method. Formally, we consider the following VAR model with time-varying parameters:

$$y_t = K_{1,t}y_{t-1} + K_{2,t}y_{t-2} + \cdots + K_{p,t}y_{t-p} + \varepsilon_t \tag{1}$$

where $K_{j,t}$, $j = 1, \dots p$ are functions of time-varying coefficient matrices, $y_t = [y_{1,t}, y_{2,t}, \dots, y_{n,t}]'$ represents an $(n \times 1)$ vector, and the idiosyncratic shocks ε_t are presumed to be heteroscedastic and serially correlated. The model consists of two endogenous variables, air-travel volume (TOT, EUR, CAR, ASIA, CAM, SAM, MIDE, OCE, AFR) and CPU, first in a bivariate setting. The null hypothesis tested is that CPU does not Granger cause US air passenger travel, formalized as $H_0: \Theta_t = 0$ for all $t = 1,2, \dots, T$, given that Θ_t is suitable subset of $vec\ (K_{1,t}, K_{2,t}, \dots, K_{p,t})$. Following Rossi and Wang (2019) we employ four test statistics; these are the exponential Wald (*ExpW*) test, the mean Wald (*MeanW*) test, the Nyblom (*Nyblom*) test, and the Quandt Likelihood Ratio (*SupLR*) test. The VAR model is estimated using a lag-length of p, as determined by the Schwarz Information Criterion (SIC), to ensure parsimony in the set-up, which allows us to work with a smaller end-point trimming to ensure longer data coverage of the time-varying test statistic. As a robustness check, we augment the predictor CPU with PC1 derived from BREER, INDPR, GPR, USEPU and GEPU in a trivariate set-up, with the PC1 explaining 41.16% variation of the five variables. As the series need to be stationary, we use the first-differences of the all variables.[9]

4. EMPIRICAL RESULTS

To analyse the predictive ability of CPU on TOT, EUR, CAR, ASIA, CAM, SAM, MIDE, OCE, or AFR in a bivariate setting, we first perform a standard Granger causality test with constant parameters, and find that CPU Granger causes MIDE, ASIA and OCE at the 5% significance level (Table 3). A weak predictive effect (at the 10% significance level) is also detected for the case of CAR.

[9] Convergence issues in the TVP-VAR model led us to use the first differences of the logarithmic transformation of the variables.

Table 3. Constant and time-varying parameter Granger causality tests in bivariate model

Dependent Variable	$\chi^2(p)$	*ExpW*	*MeanW*	*Nyblom*	*SupLR*	*SIC Lags (p)*
EUR	9.247	3960.11^{***}	2958.0523^{***}	112.3915^{***}	8809.8857^{***}	12
CAM	7.266	342.5828^{***}	352.1409^{***}	3.0115	695.8652^{***}	2
CAR	10.862^{*}	2096.704^{***}	1047.0166^{***}	80.055^{***}	5163.04^{***}	6
SAM	8.874	7206.07^{***}	1172.4513^{***}	48.0839^{***}	14364.056^{***}	5
AFR	2.887	74.8215^{***}	90.6063^{***}	4.6056	159.2341^{***}	2
MIDE	19.269^{***}	136.1612^{***}	115.0402^{***}	5.1891^{***}	283.0285^{***}	2
ASIA	15.482^{**}	1547.786^{***}	581.0725^{***}	8.3417^{***}	4053.9426^{***}	4
OCE	15.304^{***}	346.7309^{***}	385.9122^{***}	1.6529	703.3412^{***}	2
TOT	9.679	4128.664^{***}	2825.0739^{***}	110.0104^{***}	9450.9082^{***}	12

Note: The null hypothesis is that (first-differenced) CPU does not Granger cause (first difference of) the dependent variable, i.e. overseas air passenger travel, in either a constant or a time-varying VAR(*p*). ***, **, and * represents a significance of 1%, 5%, and 10%, respectively.

We then employ the *UDmax* and *WDmax* tests by Bai and Perron (2003) to detect the presence of any structural breaks in the total/eight regional overseas air passenger travel equation of the VAR(*p*) models. This procedure allows for heterogeneous error distributions across the breaks (and relevant trimming percentages based on the lags of the mode) and yield a minimum of one to a maximum of five breaks in each of the series employed. The results of these tests are reported in Table 4.

Table 4. Bai and Perron (2003) Test of Multiple Structural Breaks in bivariate models

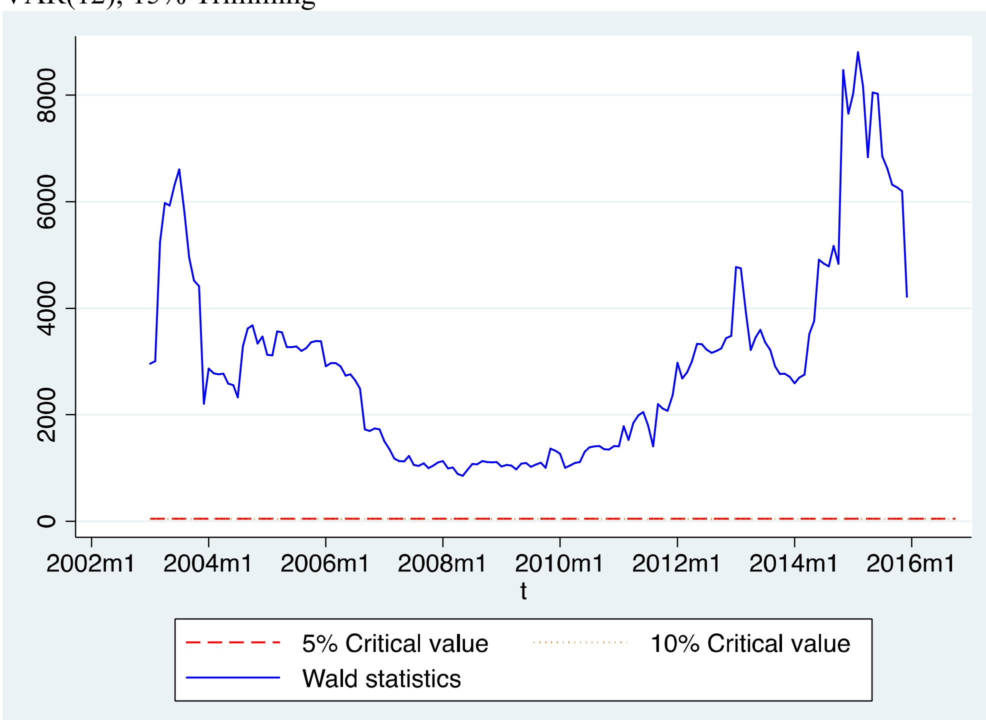
Dependent Variable in First-Differences	Independent Variable: CPU in First Differences	
	UDmax	*WDmax*
EUR	2003:11, 2009:04, 2012:01	2003:12, 2007:08, 2010:06, 2013:04, 2016:10
CAM	2010:03	2004:10, 2007:08, 2010:06, 2013:11, 2016:09
CAR	2014:02, 2017:01	2005:06, 2008:04, 2011:02, 2014:01, 2017:01
SAM	2007:01	2007:01
AFR	2003:09	2003:09
MIDE	2010:06, 2016:12	2003:09, 2007:02, 2010:04, 2013:11, 2016:09
ASIA	2003:09, 2008:03, 2011:02	2003:09, 2008:03, 2011:02
OCE	2003:04	2003:04
TOT	2003:11, 2006:09, 2009:06, 2012:03, 2016:12	2003:11, 2006:09, 2009:06, 2012:03, 2016:12

Note: Structural breaks detected from the dependent variable equation.

Given the presence of structural breaks, the use of a constant parameter model is not appropriate. As such, for reliable inference, we need to examine the *ExpW*, *MeanW*, *Nyblom*, and *SupLR* tests, which are implemented on the time-varying VAR model (these results are also reported in Table 3). Based on these tests, the null hypotheses of no-Granger causality from the CPU to the various overseas air passenger travel are rejected at the 1% significance level in at least three of the four tests (barring the *Nyblom* test statistic at times for CAM, AFR and OCE). According to these results, the predictive ability of CPU for TOT, EUR, CAR, ASIA, CAM, SAM, MIDE, OCE, or AFR is time-varying and very strong, despite the weak evidence of predictability observed when using the model with constant parameters.

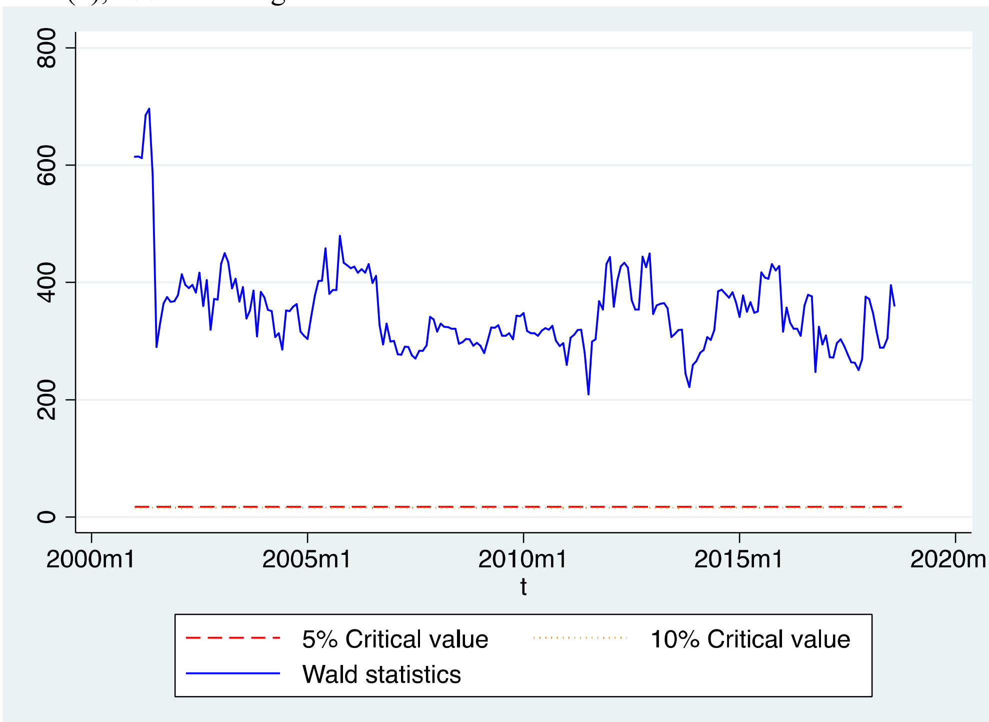
Figures 1(a) to 1(i) report the Wald statistics (whole sequence) over time, indicating when the Granger-causality occurs from CPU to the total/eight regional overseas air passenger travel. As can be seen, the uncertainty associated with climate policies is found to consistently predict the overseas tourism variables over the entire sample period. This result is not surprising given that various climate policy-related decisions were in the newspapers over this time and caused various peaks of the predictor, as observed from the annotated plot of the CPU index in Figure 2.

Figure 1(a). Time-varying Wald statistics examining whether CPU Granger-causes EUR – VAR(12), 15% Trimming



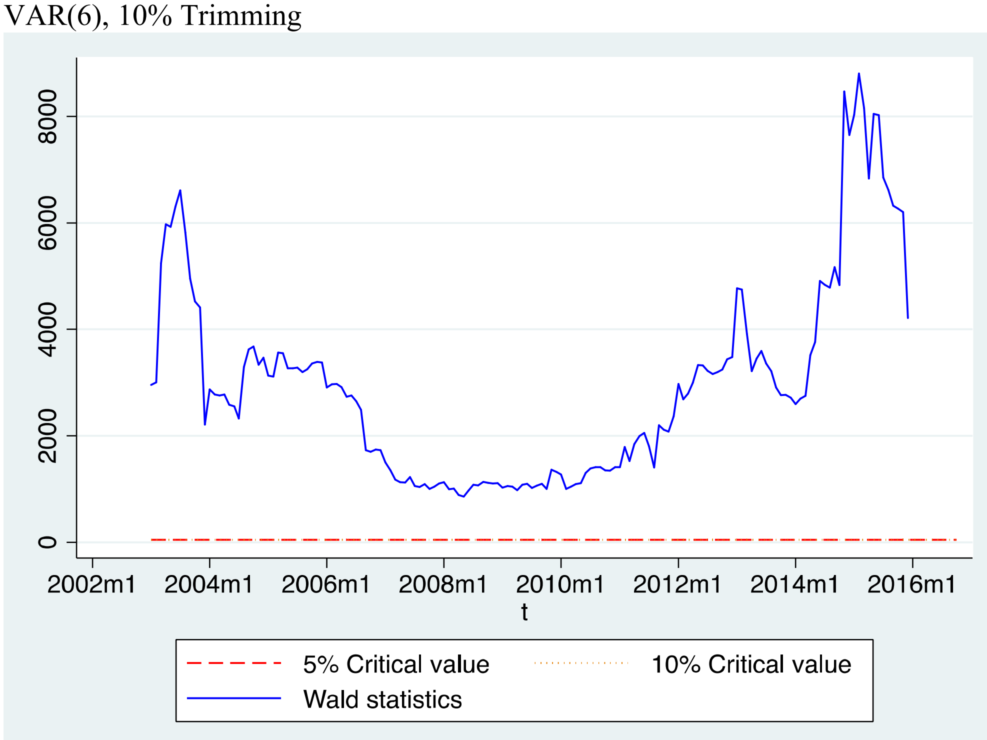
Note: x-axis corresponds to time and y-axis measures the test statistic.

Figure 1(b). Time-varying Wald statistics examining whether CPU Granger-causes CAM - VAR(2), 5% Trimming



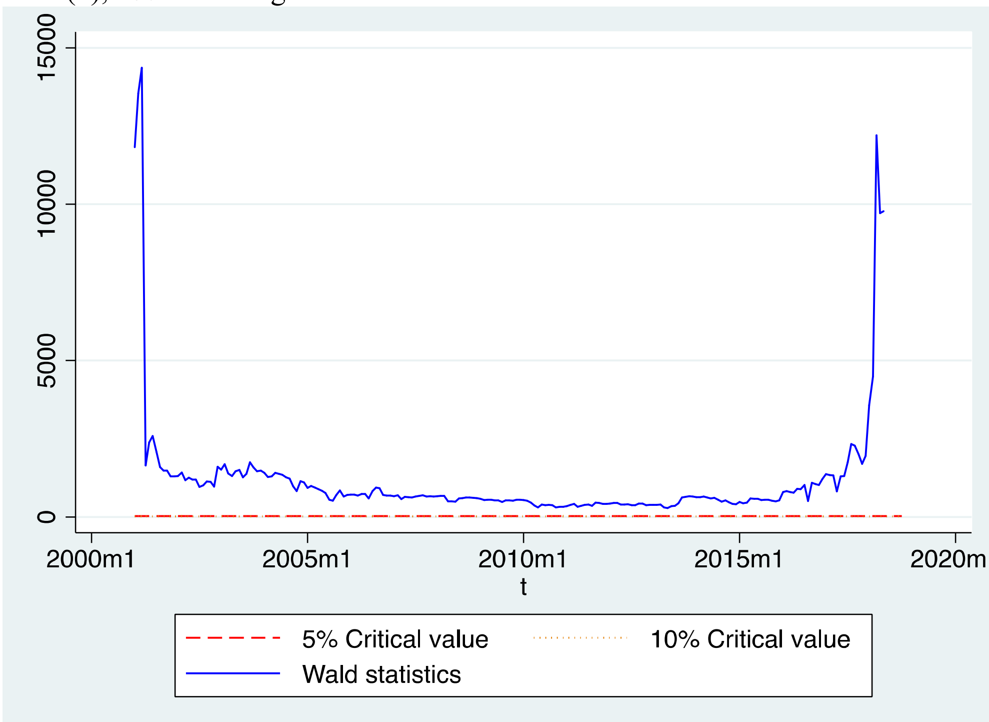
Note: x-axis corresponds to time and y-axis measures the test statistic.

Figure 1(c). Time-varying Wald statistics examining whether CPU Granger-causes CAR - VAR(6), 10% Trimming



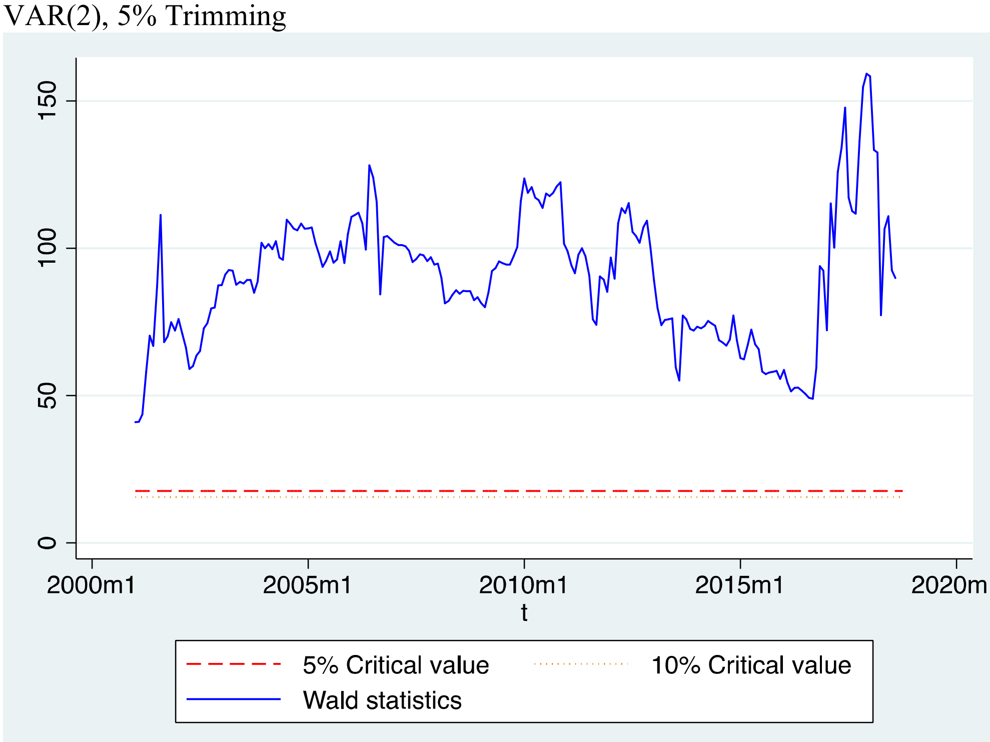
Note: x-axis corresponds to time and y-axis measures the test statistic.

Figure 1(d). Time-varying Wald statistics examining whether CPU Granger-causes SAM - VAR(5), 5% Trimming



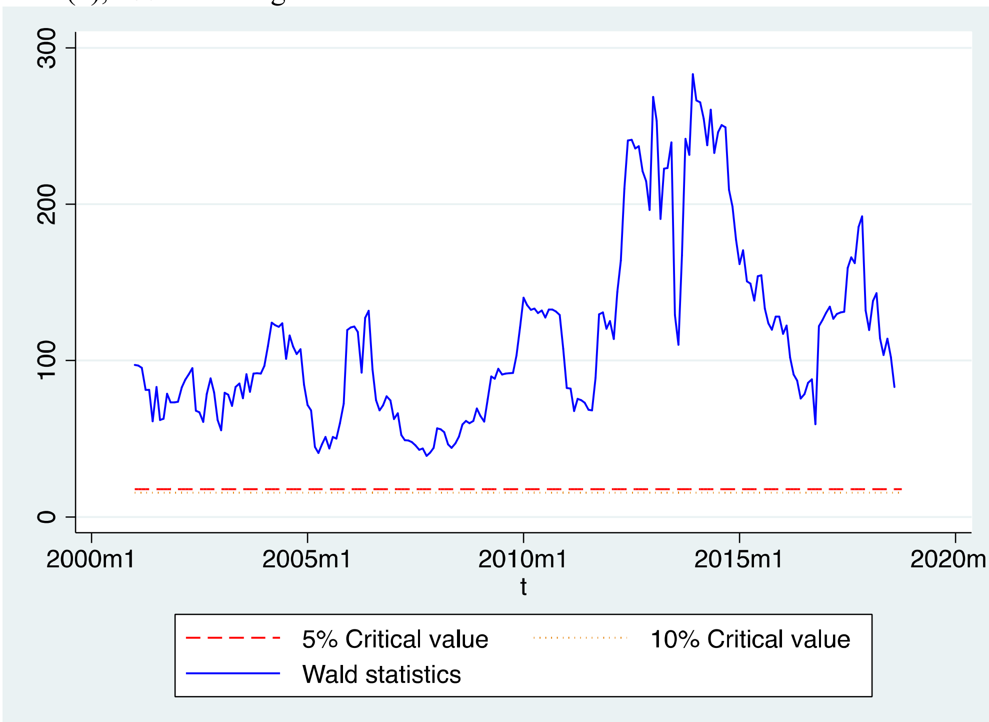
Note: x-axis corresponds to time and y-axis measures the test statistic.

Figure 1(e). Time-varying Wald statistics with, testing whether CPU Granger-causes AFR - VAR(2), 5% Trimming



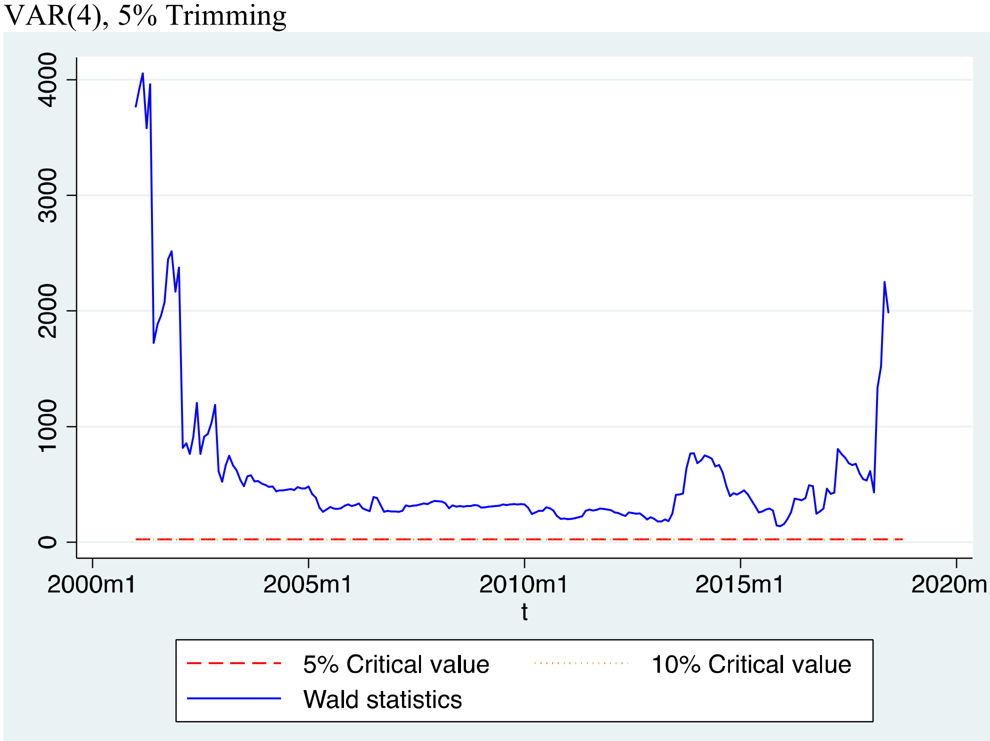
Note: x-axis corresponds to time and y-axis measures the test statistic.

Figure 1(f). Time-varying Wald statistics examining whether CPU Granger-causes MIDE - VAR(2), 5% Trimming



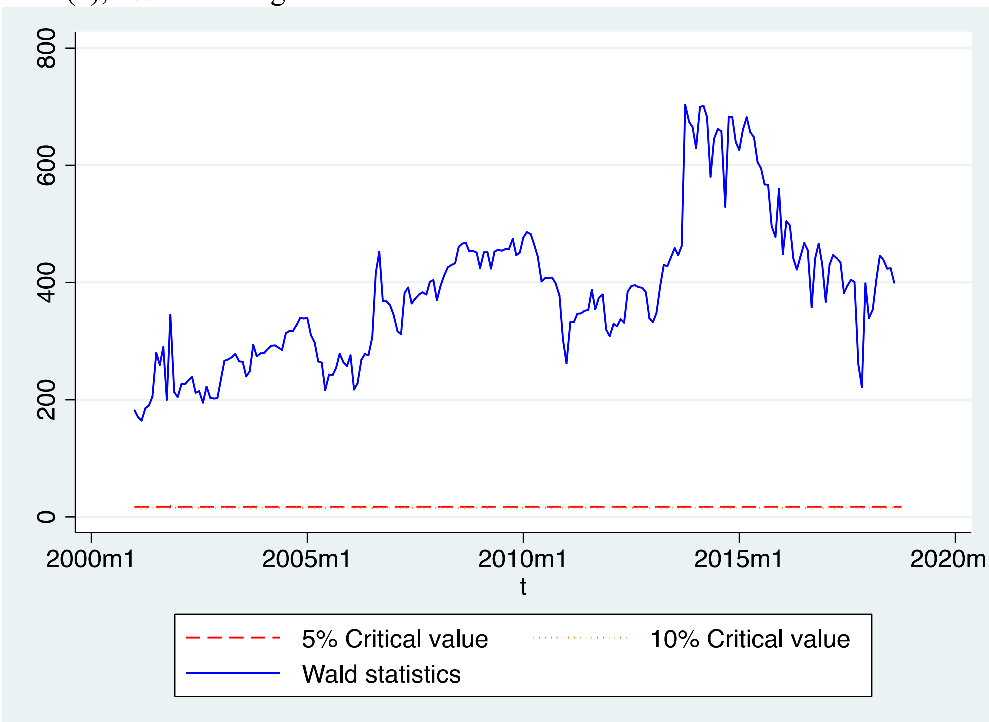
Note: x-axis corresponds to time and y-axis measures the test statistic.

Figure 1(g). Time-varying Wald statistics examining whether CPU Granger-causes ASIA - VAR(4), 5% Trimming



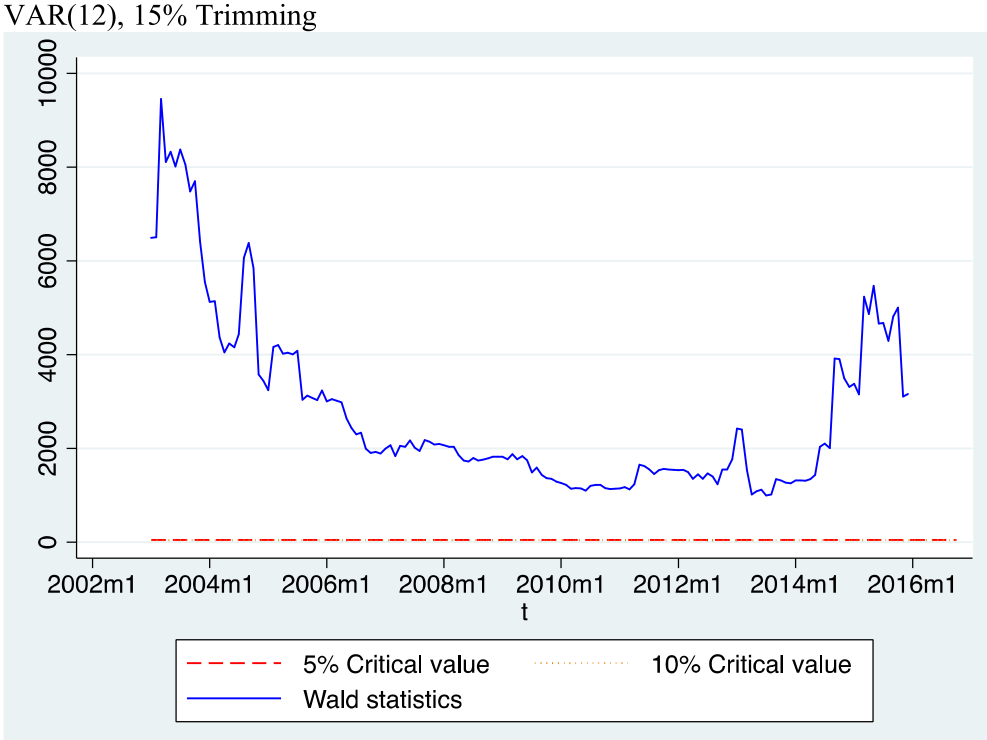
Note: x-axis corresponds to time and y-axis measures the test statistic.

Figure 1(h). Time-varying Wald statistics examining whether CPU Granger-causes OCE - VAR(2), 5% Trimming



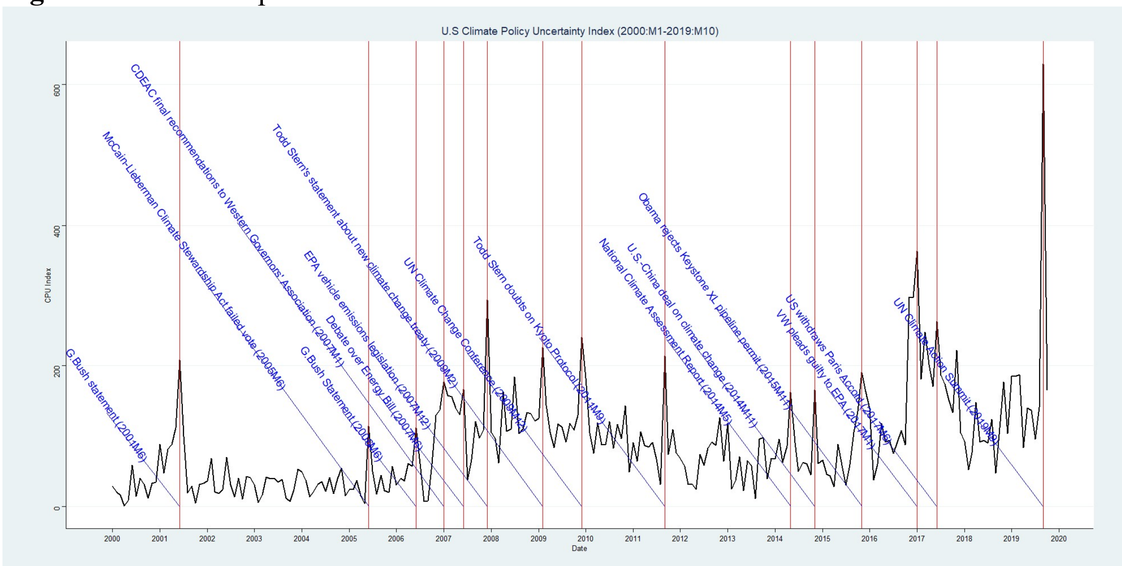
Note: x-axis corresponds to time and y-axis measures the test statistic.

Figure 1(i). Time-varying Wald statistics examining whether CPU Granger-causes TOT - VAR(12), 15% Trimming



Note: x-axis corresponds to time and y-axis measures the test statistic.

Figure 2. Annotated plot of the CPU Index



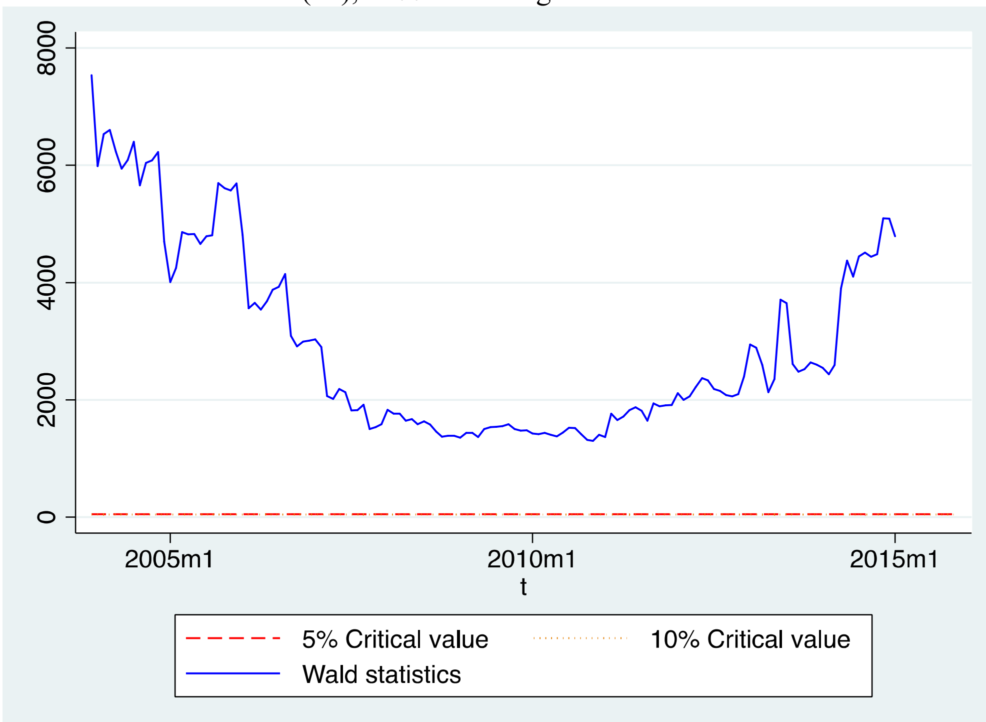
As a robustness check, in Table 5, we report the results from the time-varying causality test, with the PC1 used as a control in a trivariate setting. The results remain similar to those obtained in a bivariate framework, providing strong evidence of the in-sample predictability of the climate policy-related uncertainty, to the overall and regional overseas air passenger travel of US citizens, based on at least three of the four tests considered. In addition, as can be seen from Figures 3(a) to 3(i), reporting the Wald statistics over time for the trivariate setting, causality continues to hold at each point in time, even when we use the control variable, i.e. the PC1, which summarizes the information content of the various other predictors (involving macroeconomic factors and other metrics of uncertainty and geopolitical risks) suggested by Apergis and Payne (2020).

Table 5. Time-varying parameter Granger causality tests in trivariate setting

Dependent Variable	*ExpW*	*MeanW*	*Nyblom*	*SupLR*	*SIC Lags (p)*
EUR	3894.7203***	3044.1506***	234.8922***	8405.1182***	12
CAM	714.2418***	434.3558***	3.6706	1704.6991***	2
CAR	520.4555***	462.8328***	2.9106	1051.6139***	2
SAM	1542.0341***	956.6913***	27.4924***	3641.9187***	4
AFR	188.254***	137.0315***	6.875***	387.2164***	2
MIDE	267.7938***	190.73***	6.7958***	546.296***	2
ASIA	131.2365***	76.4564***	2.5182	273.1899***	1
OCE	396.4763***	412.342***	2.9122	803.5924***	2
TOT	162.08***	144.7515***	3.8306	334.8526***	2

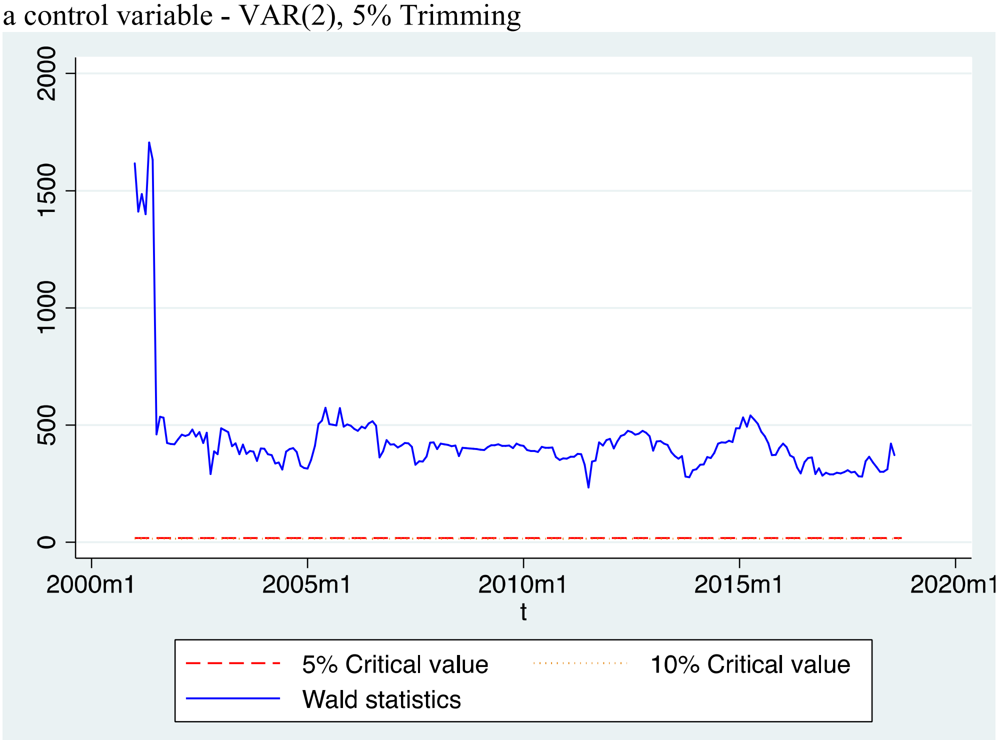
Note: See Note to Table 1. The third variable in the system is the principal component of the first differences of BREER, INDPR, GPR, USEPU and GEPU.

Figure 3(a). Time-varying Wald statistics examining whether CPU Granger-causes EUR with a control variable - VAR(12), 20% Trimming



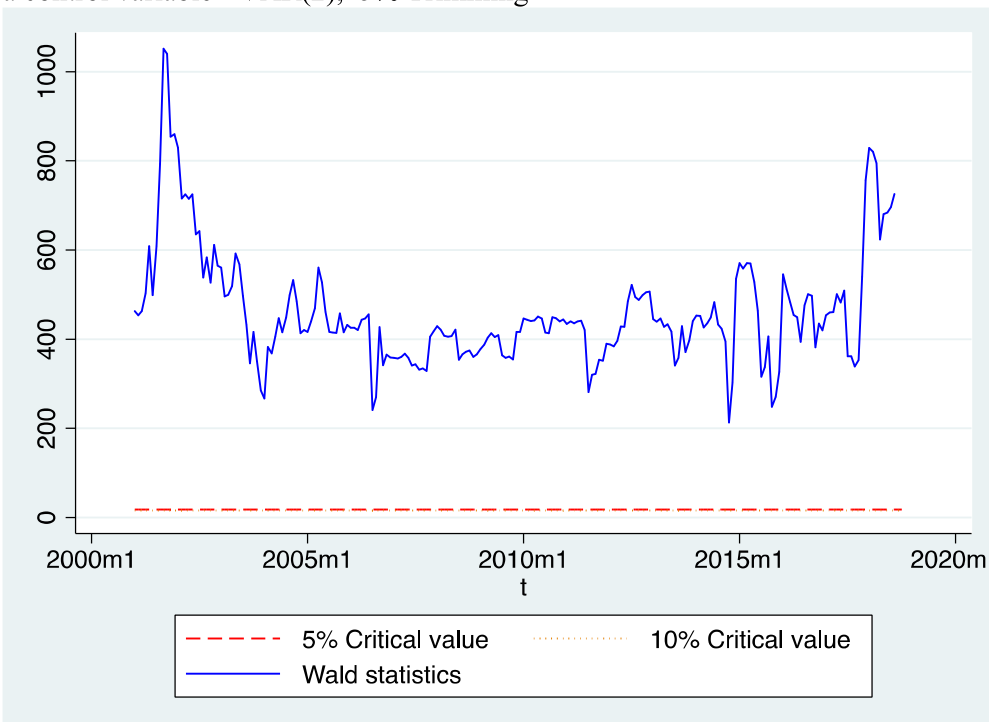
Note: x-axis corresponds to time and y-axis measures the test statistic.

Figure 3(b). Time-varying Wald statistics examining whether CPU Granger-causes CAM with a control variable - VAR(2), 5% Trimming



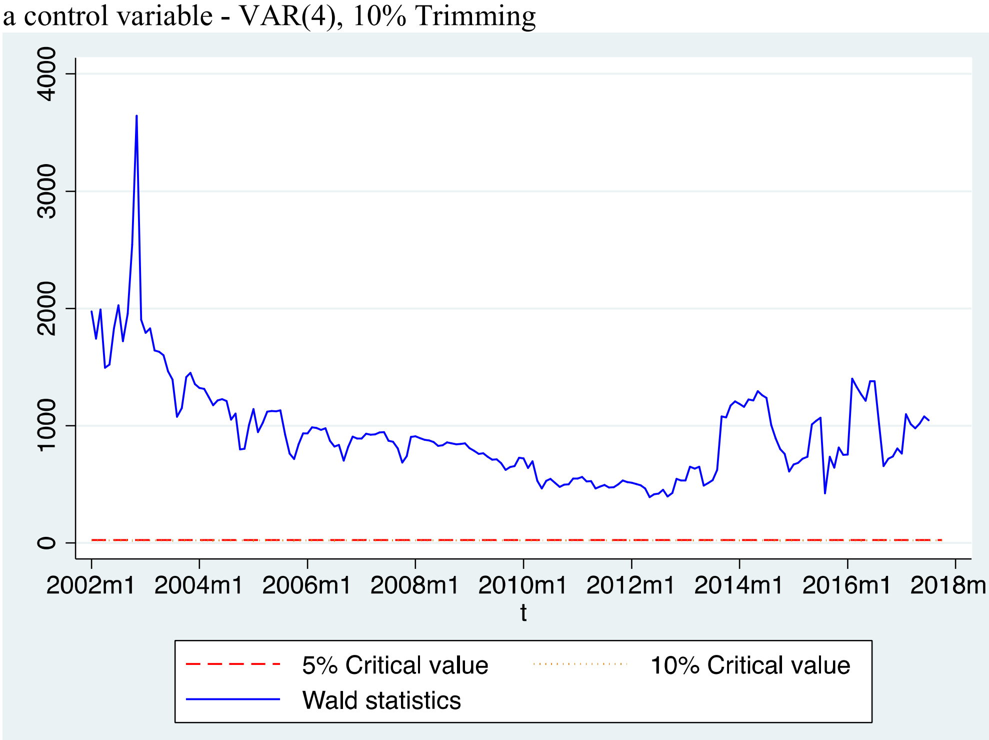
Note: x-axis corresponds to time and y-axis measures the test statistic.

Figure 3(c). Time-varying Wald statistics examining whether CPU Granger-causes CAR with a control variable - VAR(2), 5% Trimming



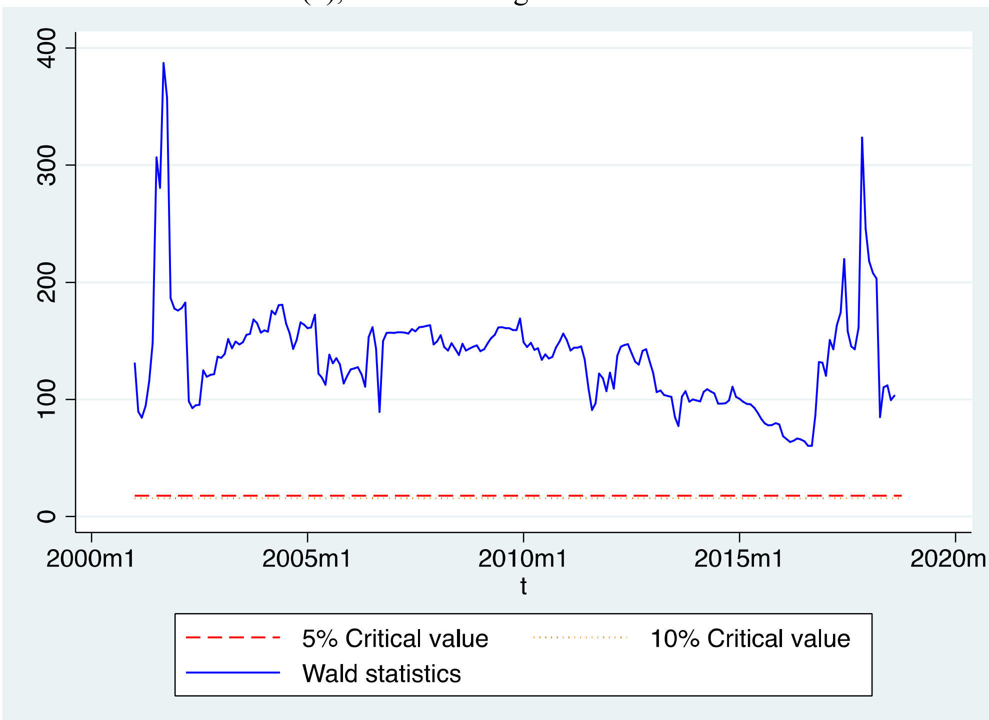
Note: x-axis corresponds to time and y-axis measures the test statistic.

Figure 3(d). Time-varying Wald statistics examining whether CPU Granger-causes SAM with a control variable - VAR(4), 10% Trimming



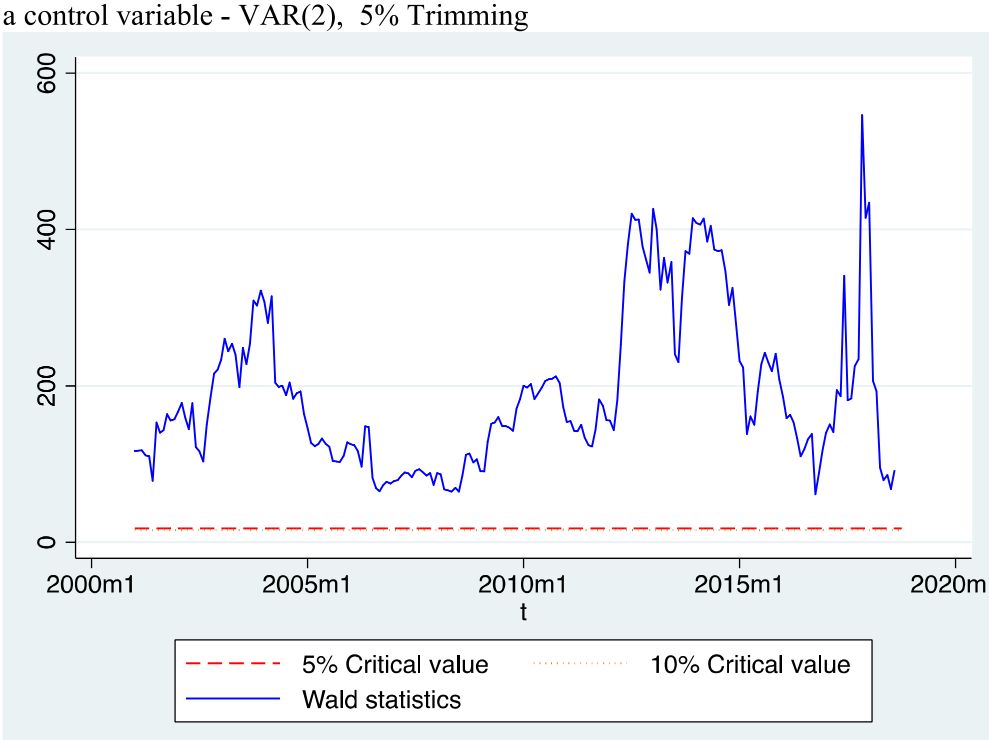
Note: x-axis corresponds to time and y-axis measures the test statistic.

Figure 3(e). Time-varying Wald statistics examining whether CPU Granger-causes AFR with a control variable - VAR(2), 5% Trimming



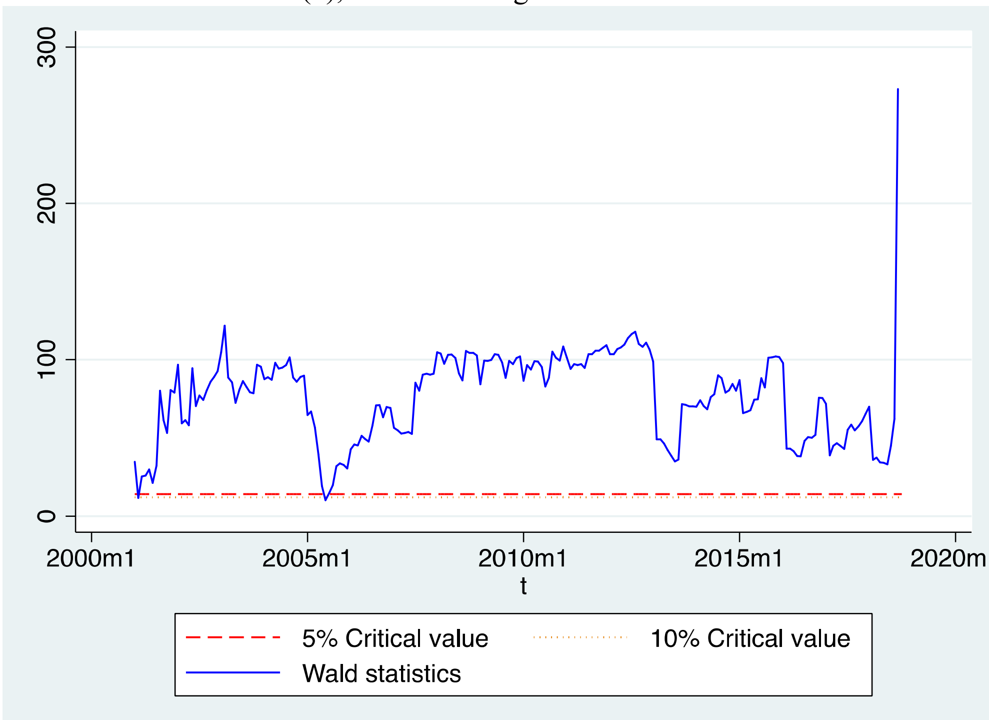
Note: x-axis corresponds to time and y-axis measures the test statistic.

Figure 3(f). Time-varying Wald statistics examining whether CPU Granger-causes MIDE with a control variable - VAR(2), 5% Trimming



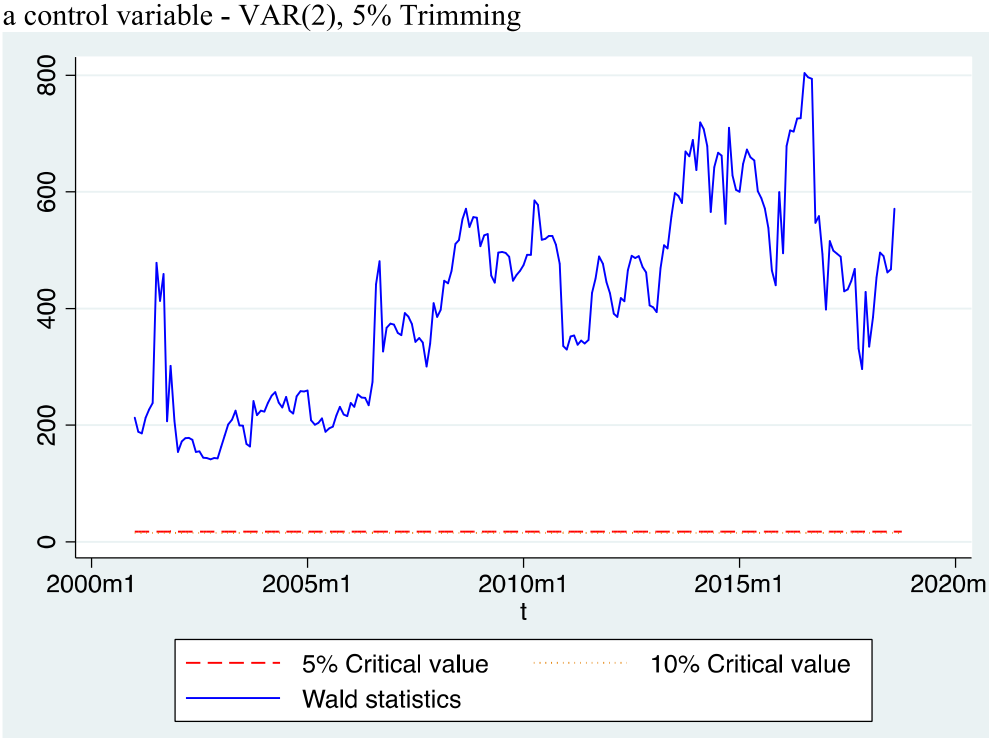
Note: x-axis corresponds to time and y-axis measures the test statistic.

Figure 3(g). Time-varying Wald statistics examining whether CPU Granger-causes ASIA with a control variable - VAR(1), 5% Trimming



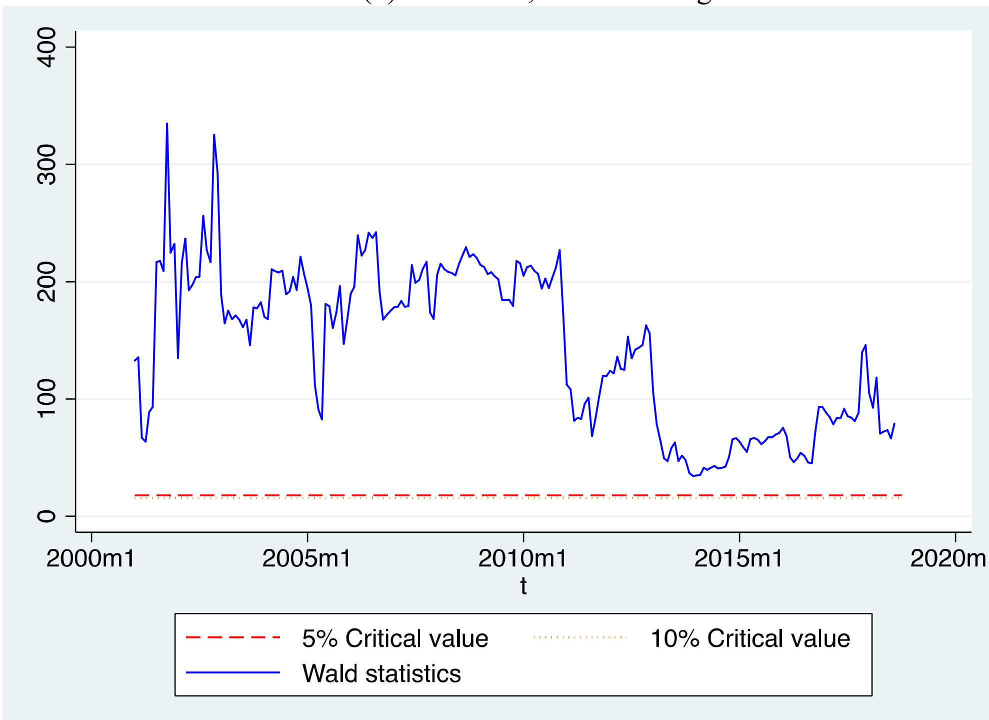
Note: x-axis corresponds to time and y-axis measures the test statistic.

Figure 3(h). Time-varying Wald statistics examining whether CPU Granger-causes OCE with a control variable - VAR(2), 5% Trimming



Note: x-axis corresponds to time and y-axis measures the test statistic.

Figure 3(i). Time-varying Wald statistics examining whether CPU Granger-causes TOTOVR with a control variable - VAR(2) under SIC, 5% Trimming



Note: x-axis corresponds to time and y-axis measures the test statistic.

5. CONCLUSION

Tackling climate change has been at the forefront of the world community and national policy makers. Despite that tourism has been one of the most important drivers of economic growth, it is also one of the largest emitting industries. As such, uncertainty surrounding climate policies can have a major impact on the demand for tourism activities; the channels through which this can happen are mainly two. First, such policies may increase the cost of travelling and other related tourism activities, making such activities more expensive. Secondly, climate policies could change travellers' attitude towards travelling by increasing their environmental awareness and hence, their propensity to travel to long destinations.

This study examines for the first time in the literature the impact of climate policy-induced uncertainty on tourism demand. Specifically, it adopts the Rossi and Wang (2019) approach to analyse the time-varying impact of US climate policy uncertainty, proxied by the CPU index, on air-travel demand to eight regional overseas destinations. Our findings indicate that CPU is an important determinant of tourism demand over the entire sample period of 2000:01-2019:10. Interestingly, this strong evidence is only observed under a time-varying setting and not under the constant parameter Granger causality test. The latter yields weak results given its inability to detect multiple structural breaks in the relationship between CPU and US air-travel demand, which we detect using formal statistical tests.

The evidence presented in this study bears important implications for destination countries and tourism professionals. More specifically, as policies tackling climate change are being introduced and people become more environmentally conscious, it is suggested that tourism destinations, which are more vulnerable to climate change and are affected more by such policies (e.g., distant island destinations), to try and alleviate their carbon footprint by promoting more sustainable forms of tourism. In that sense, the policymakers in the tourism industry should explicitly account for climate conditions when discussing strategies to cope with climate change. This could help tourism services to better and more efficiently monitor the changes in the perception and attitudes of foreign tourists. Finally, future research might incorporate the CPU index into forecasting models in order to improve their accuracy and predictive capacity, thus providing tourism-policy makers with an additional tool in their effort to predict tourist arrivals; yet, notion needs to be taken about the existence of structural breaks in the relationship between CPU and tourism demand.

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