Supply Side Sentiments and International Travel: A Novel Dynamic Simulation of Policy Options for Business and Investor Sentiments

Highlights

1. Using a forward-looking model, we find that travel export service in the USA is more sensitive to shocks in consumer confidence than investor sentiment.
2. Stakeholders should pay attention to the adverse impact of business sentiments to travel service exports in the USA in the long term.
3. Investor sentiment measure outweighs consumer sentiment measures in terms of impact in the short term.
4. Travel services will decline in the next decade and this downturn will be exacerbated by sentiment

Abstract

Using a forward-looking forecasting model, this article investigates the interplay between various sentiment measures and travel for periods after the Covid-19 pandemic. The study employed the novel dynamic autoregressive distributed lag model (dynARDL) while presenting various simulations of variable inclusion or exclusion. The simulation robustly accounts for the effect of trade, real GDP, and foreign direct investment on travel services. The result shows a long-term relationship between travel services and customer sentiment. In other words, an increase in the bull-bear spread (BBS), in the short-run, has a negative influence on travel services, but this link fades in the long-run. Consumer confidence, on the other hand, has a positive impact on travel services in both the short and long-run. Our findings advocate the consideration of sentiments when modelling travel services export. The forecasting model also reveals that travel services will decline in the future.

Keywords: Tourism, Travel Services, Forecasting, Investors' Sentiment, Business- Sentiment.

1. Introduction

One of the adverse consequences of the coronavirus epidemic has been the stifling of growth in travel and travel services. For countries that are overly reliant on tourism, relevant knowledge on recovery from the pandemic would be of great value. In this light, recent evidence in the tourism literature indicates that the impact of mood and psychology on tourism demand could be sensitive to socioeconomic events (Dragouni *et al.*, 2016). Hence, studies that focus on mood, psychology and tourism are timely and could provide valuable insights that would help build back better from the wreck of the pandemic. It is in this spirit that we examine how shocks in various measures of sentiments affect travel-related services using a forward-looking forecasting model (i.e. novel dynamic autoregressive distributed lag model).

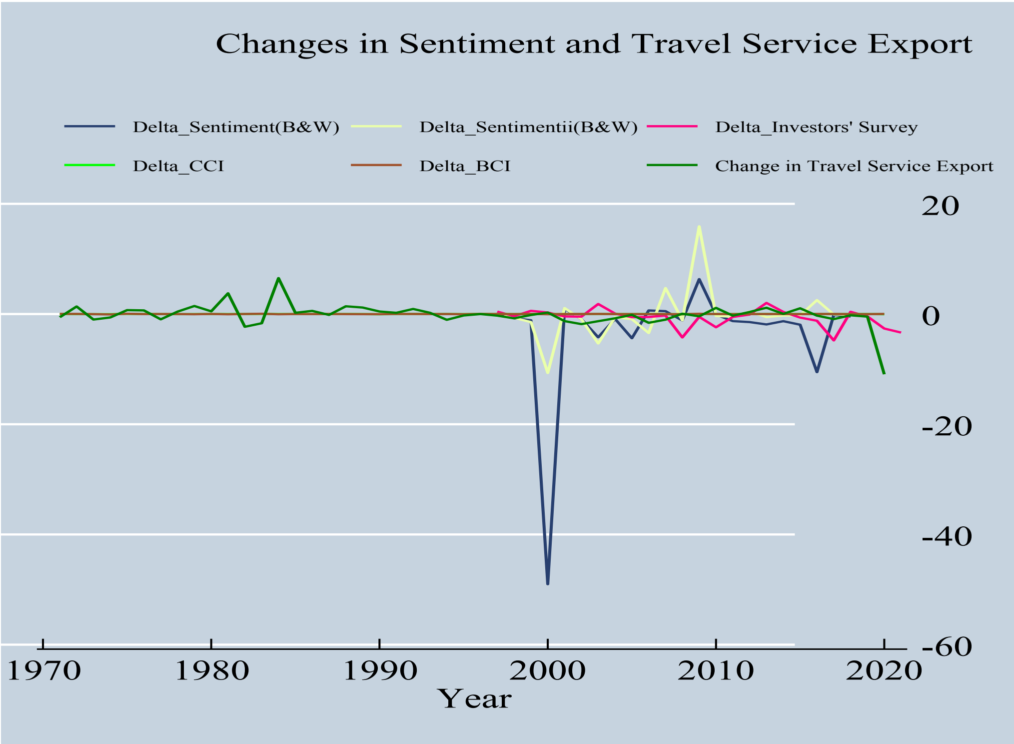
In general, the literature on travel and sentiment documents linkages between mood, optimism, pessimism, and tourism. For instance, Gholipour and Foroughi (2020), demonstrate that business optimism is a significant determinant of international travel and tourism expenditure. Unlike "hard" variables (e.g., gross domestic product, general price index) that offer limited advantages to modelling tourism, sentiment measure improves the goodness of fit and predictive accuracy of time series models (Guizzardi and Stacchini, 2015). Accordingly, Liu *et al.*, (2019) reveal that the unique sentiments of Chinese tourists affect travelling decisions. Using tourism reviews by Chinese travellers, they demonstrate that international traveller sentiments are distinguishable and are important determinants of the supply-side policy of tourism. Similarly, various indicators of sentiment and mood could influence outbound tourism demands, the magnitude of their effect is time-varying and differs with socioeconomic and environmental circumstances (Dragouni *et al.*, 2016).

The interplay between travels, sentiment and the COVID-19 pandemic is constantly evolving. For instance, restrictive measures like lockdowns, mandatory isolation, and limitations on travel could increase the demand for tourism products (Lu and Zheng, 2021). Insights from both demand side and supply side sentiments are important components for deciphering the dynamism of the relationship.

Empirical evidence suggests that the relationship between consumer expectations regarding their future financial health as well as the economy at large and outbound tourism decreased over time. In contrast, macro measures of tourism like the Economic Policy Uncertainty (EPU) transmitted spillover to tourism both before and after the global financial crisis (Dragouni *et al.,* 2016). Although the EPU measures capture the future expectation of the economy, it omits irrational exuberance. Investor sentiment, in contrast to EPU, is an anticipation of the future situation of the capital market that is not supported by the fundamental information about the market (Baker and Wurgler, 2007). Therefore, embedded in investor sentiment are unique psychological features that are valuable for modelling movements in travels.

Confirming our conjecture, *Figure I* indicate that shocks to most measures of sentiment coincide with changes in travel services export. Accordingly, changes in investors' surveys mimic shocks to travel services export effectively. This confirms the argument that macro-based measures may be better barometers for modelling travels than consumer and managers' surveys (Dragouni *et al.,* 2016).

Figure I: Changes in Sentiment and Travel Services Export



Contrary to previous studies that look at how changes in stock market performance and business sentiment indicators (BSI) affect outbound tourism (see, for instance, Guizzardi and Stacchini, 2015; Dragouni *et al.,* 2016; Gholipour and Foroughi, 2020), we probe the linkages between changes in a unique measure of sentiment (i.e., investor sentiment) and travel services as a proportion of export. To the best of our knowledge, this will be the first research to use aggregate stock market and investor survey data to quantify sentiment in a travel or tourism-related study. We present new evidence on the influence of several sentiment measures on travel as an export commodity. Primarily, we pose the question; how informative are various categories of sentiment shocks to travel services? We also reflect on the question: Will sentiment be important for modelling travels in the post-covid-19 era? Insights from our study form important pillars that tourism-dependent economies can build on amidst the negative impact of the coronavirus pandemic on travel and its complementary services.

Inferences from this study are important building blocks that could alleviate the adverse effect of the COVID-19 pandemic on tourism since we unlock a new frontier of knowledge on the impact of shocks to sentiments on travel and ad-hoc services as a percentage of export.[1] In addition, this study is a response to the call to action for studies within the COVID-19 tourism research cluster to evaluate deeply, the dynamics of behaviour, emotion, psychology, and ideology in shaping the choices of tourism stakeholders (Sigala, 2020). We also address the need for tourism studies in response to COVID-19 to be multidisciplinary, interdisciplinary, and anti-disciplinary (Sigala, 2018, Wen *et al.*, 2020, Gossling *et al.*, 2020, Hall *et al.,* 2020). Our study also represents a significant leap in research design and methodology. In this strand of the literature, we represent the first application of the novel dynamic autoregressive distributed lag model (dynARDL). We demonstrate how the dynARDL model can be used to answer questions about the future of travel and tourism.

Our results indicate that consumer sentiment will be important for modelling changes in travel as a percentage of export in the short run and long run (post-covid-19 era). In the short run, we document that investor sentiment (BBS) is an important determinant of travel services. In terms of impact, we document that a shock to consumer sentiment influences travel services at a greater magnitude than investor sentiment. The simulation also indicates that travel services will decline in the future. Our findings have important implications for stakeholders. Firstly, for policymakers, when estimating long and short-term variation in travel services, the impact of tourism differs by category. For tourism-dependent countries, our findings reemphasize the call for economic diversification since the model demonstrates a future decline in travel.

[1] Regarding the enormity of losses as a result of the pandemi, it is estimated that the pandemic has caused a loss of $1.2 trillion in export revenues that are attributable to tourism (UNWTO, 2020).

The remainder of this work is structured as follows. Section 2 is an assessment of the related literature. Section 3 goes into the data and technique used in this research. Section 4 examines our findings and discusses the study's consequences. Section 5 brings the research to a close.

2. 0 Literature Review

2.1 Theoretical Framework

Leading indicators are instrumental for modelling critical periods during bad economic cycles; they are also effective for forecasting future economic activity (Diebold and Rudebusch, 1989; Estrella and Trubin, 2006). These signals can be deciphered from the mood of the participants of the economy such as consumers and investors. To this effect, the psychology literature provides extensive discussions on the role of emotions, moods and feelings in decision making (see, for instance, Schwarz and Clore, 1983; Loewenstein *et al.*, 2001).

Theoretically, consumers may demand more luxury goods if they are in a good mood and are optimistic about the future economic outlook (Katona, 1975,1980; Gardner, 1985). A significant portion of this optimism is driven by consumer expectations of their wealth albeit these beliefs are not necessarily rational (Malgarini and Magani, 2007). Therefore, if consumers are positive about their future earnings, then they would favour spending more on expensive goods and services such as tourism. Complementing this view, several studies document a significant relationship between consumer sentiment measures and consumer spending. For instance, Bryant and Macri (2005) find that consumer sentiment affects their spending behaviour. However, one of the drawbacks of consumer sentiment measures is that it is a poor predictor of consumer spending during periods of heightened consumer sentiment, similarly, consumer sentiments are subjective to income groups and political associations (Nguyen and Claus, 2013).

2.2 Business and Investor Sentiments and the Tourism Industry

In the travel and tourism literature, Crotts *et al.*, (1993), one of the early studies to consider the relationship between consumer sentiment and travel volumes, find that consumer confidence is an important indicator of changes in levels of travel in the USA. Order than consumer confidence, the wealth of consumers' investment portfolio also affects their spending on travels. In Korea, the unrealised wealth effect from the housing market plays an important role in travel decisions (Kim *et al.*, 2012). This implies that the wealth effect on the portfolio of consumers whether realised or unrealised significantly affects their marginal propensity to consume travel services. Tourism demand could also be driven by social networks, people are likely to travel to countries where they have social ties (Gavriilidis, 2020). Similarly, Gholipour and Foroughi (2020), using a sample of 40 countries reveal that the level of consumer confidence is an important determinant of outbound business travels. However, the effect of consumer survey-based measures diminishes over time (Dragouni *et al.*, 2016).

Despite the obvious theoretical linkages between investor sentiment and travel, the literature on the relationship between investor sentiment and tourism is scant. For instance, in a recent study, Zargar and Kumar (2021), use the Standard and Poor's 500 (S&P 500) as a measure of investor mood document that investor mood and sentiment are key drivers of shocks to travel and leisure stocks. In essence, firms in this sector fare poorly when investors are in a bad mood. Similarly, Dragouni *et al.* (2016) demonstrate that social mood is the key driver of shocks to outbound tourism in the early years of the global financial crisis (GFC) and for the period 2005-2006. In effect, the relationship between sentiment, mood and tourism is sensitive to time and event. Dragouni *et al.* (2016) also adopt the S&P 500 as a barometer for social mood.

Whilst stock market indices are good gauges of social mood (Nofsinger, 2005), they are not efficient proxies for measuring investor sentiment. This is because movements in stock markets are dictated by changes in investor sentiment (Baker and Wurgler, 2007). Therefore, a stock index is merely an indirect measure of investor sentiment. Accordingly, we contribute to the investors' sentiment-tourism nexus by using direct measures of investor sentiment. To the best of our knowledge, the proxies of investor sentiment used in this study are deployed for the first time in the tourism literature. Investor sentiment is an important leading factor for modelling tourism because signals about investor perceptions on their future wealth can be deduced. These signals can manifest as positive or negative shocks to social moods which can affect demand and supply of travel and ad-hoc services.

2.3 Other determinants of international travel

The income in the origin country could affect the demand for tourism and adjunct travel services. Higher wages in the destination country relative to origin countries could drive up the cost of travel and supplementary services thus dissuading tourists (Halicioglu, 2010; Martin *et al.*, 2017). Similarly, lower wages in the destination country could encourage inbound travel. Moreover, since tourism can be termed a luxury good (Kim *et al.,*2012), the travel demand will be dictated by the income of holidaymakers. To capture income, most studies in the literature employ gross domestic product (GDP) or gross national product per capita (GNP) as measures of income (see, for instance, Halicioglu, 2010; Martins *et al.*, 2017).

The comparative price of tourism in similar destination countries could also influence travel decisions (Dwyer *et al.*, 2002). The rational expectation is that *ceteris paribus*, tourists will favour cheaper locations. A popular measure adopted by studies in the tourism literature is adjusting the inflation rate (i.e., consumer price index) in the destination country by that of the country of origin whilst correcting for exchange rate differences (Oh and Ditton, 2005; Gounopoulos *et al.*, 2012; Martins *et al.*, 2017).

The trade openness of the destination country significantly affects the tourist receipts of the country (Khoshnevis *et al.*, 2017). In contrast, Shahbaz *et al.* (2017), find that there is reverse causality between trade openness and tourism. Similarly, the relationship between foreign direct investment (FDI) and tourism could be bidirectional (Craigwell and Moore, 2008). Confirming this view, Li *et al.* (2017), reveal that overseas investment in tourism by China is significantly impacted by the level of tourism flow from the host country. Similarly, Tang *et al.* (2007), using Chinese data document a causal relationship between tourism and FDI.

In recent times, studies in the tourism literature have also explored the link between non-conventional macroeconomic variables and tourism; results in this strand of the literature make a strong case for modelling tourism from the lenses of non-conventional measures. For instance, Goh *et al.* (2008) find that demand for tourism is more sensitive to climate, leisure, and time than regular macroeconomic determinants. Similarly, the climate condition in the country of origin could also affect their outbound choices. Accordingly, tourist's resident in countries or regions with a good climate index are less likely to travel abroad but are more likely to choose domestic destinations for their vacations (Eugenio-Martin and Campos-Soria, 2010). Correspondingly, the level of personal freedom could also affect the demand for tourism. Confirming this view, Gholipour *et al.*, (2014), demonstrate that restrictions in freedom in the country of origin could increase demand for overseas travel. Other factors such as climate condition, habits, marketing, political stability, and significant events like terrorist attacks have been shown to affect tourism (Cazanova *et al.,* 2014; Kronenberg *et al.*, 2015; Lorde *et al.*, 2015).

3.0 Data and Methods

3.1 Data and Variables

The variables employed and the ensuing data as it relates to this study as well as the sources of the data is displayed in the table 1. Travel services refer to the value of goods and services acquired by travellers to the USA during their visit. Trade (% US GDP) equals the sum exports/imports of good/services deflated by the GDP. GDP per capita is deflated by the population of the USA at midyear. FDI refers to the net inflows of investment aimed at acquiring long term interest in an enterprise in a country other than that of the investor.

Table 1: Description of Variables

Variable	Abbreviation	Source
Travel services (% of service exports, BoP)	TRAV	International Monetary Fund
Trade (% of GDP)	TRAD	World Bank
GDP per capita (constant 2015 US$)	RGDP	World Bank
Foreign direct investment, net inflows (% of GDP)	FDI	International Monetary Fund
BCI	BCI	OECD
CCI	CCI	OECD
Bull-Bear (Spread)	BBS	American Association of Individual Investors

Macro Sentiment Measure B&G	BGS1	Baker and Wurgler (2006)
Macro Sentiment Measure II B&G	BGS2	Baker and Wurgler (2006)

BCI is an indicator of business confidence, it is inferred from surveys on changes in production, orders as well as changes in stocks. CCI provides information on the future development of household consumption and savings as well as their sentiment on the general economic outlook. Bull-Bear Spread (BBS) offers insights into the mood of investors. Sent_1B&G & Sent_2B&G are measures of sentiment deduced from macroeconomic indicators (Baker and Wurgler 2006).

Table 2: Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
LTRAV	34 Years	3.28557	0.2489582	2.333936	3.596992
LTRAD	34 Years	3.187928	0.154084	2.888903	3.432563
LRGDP	34 Years	10.79141	0.1520591	10.51258	11.01595
LFDI	34 Years	0.3650466	0.4654582	-0.7660319	1.225338
LENU	34 Years	8.860645	0.0218636	8.823991	8.896452
BCI	34 Years	99.81786	1.359741	95.63475	102.0098
CCI	34 Years	100.1315	1.557022	96.33633	102.7271
BBS	34 Years	0.0723341	0.089763	-0.1298077	0.2521137
BGS1	34 Years	0.1901302	0.6043989	-0.7685655	2.253173
BGS2	34 Years	0.1089351	0.6256274	-0.8473941	2.063269

The BCI variable has a mean value of 99.81786 and a minimum of 95.63475, and maximum of 102.0098 with 1.359741 as the deviation indicating the degree of dispersion between the mean and the actual data observed for estimation. Periods with BCI values above 100 indicates optimism about the future economic outlook while a value below 100 suggests pessimism about the future economic state. The CCI variable has a mean value of 100.1315 and a minimum and maximum value of 96.33633 and 102.7271 respectively with a dispersion of 1.557022. The Bull-Bear Spread (BBS) variable has a mean value of 0.0723341 and a minimum and maximum value of -0.1298077 and a maximum value of 0.2521137 with a standard deviation of 0.089763. Periods with positive values indicate high optimism by investors while periods with negative values indicate pessimism by investors as regards market valuation. The BGS1 variable has a mean of 0.1901302 and a minimum of -0.7685655, maximum of 2.253173 with 0.6043989 as the standard deviation. Finally, on average, the mean of the BGS2 is 0.1089351, minimum is -0.8473941, maximum is 2.063269 and dispersion is 0.6256274 indicating lesser dispersion between the mean and the observed data for estimation.

The correlation matrix, in the table 3, depicts the magnitude and direction of the relationship existing between each pair of the variable to be analysed in the table below.

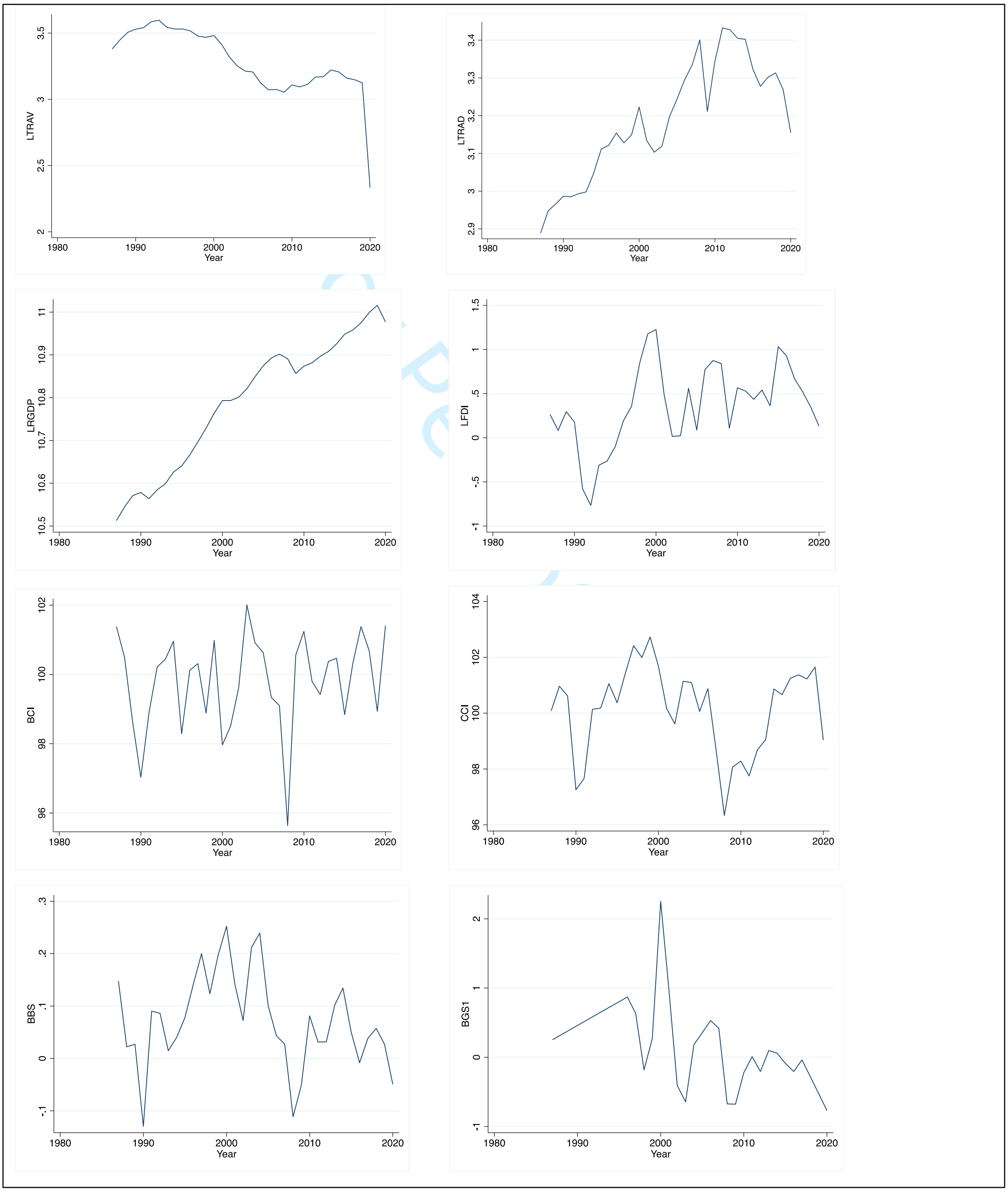
Table 3: Correlation Matrix

	LTRAV	LTRAD	LRGDP	LFDI	BCI	CCI	BBS	BGS1	BGS2
LTRAV	1								
LTRAD	-0.5781*	1							
	0.0003								
LRGDP	-0.7603*	0.8664*	1						
	0.0000	0.0000							
LFDI	-0.27	0.5784*	0.5469*	1					
	0.1225	0.0003	0.0008						
BCI	-0.203	-0.0758	0.0966	-0.204	1				
	0.2495	0.67	0.587	0.2473					
CCI	0.3131	-0.1749	-0.0119	0.2085	0.3846*	1			
	0.0714	0.3226	0.9468	0.2366	0.0247				
BBS	0.3386	-0.0832	-0.1037	0.1362	0.3592*	0.6237*	1		
	0.0502	0.6401	0.5596	0.4423	0.0369	0.0001			
BGS1	0.6340*	-0.3175	-0.4936*	-0.0167	-0.2231	0.2807	0.4289*	1	
	0.0001	0.0673	0.003	0.9253	0.2047	0.1078	0.0114		
BGS2	0.7020*	-0.434*	-0.5995*	-0.084	-0.2755	0.2658	0.3863*	0.9748*	1
	0.0000	0.0104	0.0002	0.6368	0.1148	0.1286	0.024	0.0000	
* Represents 5% level of significance									

It depicts that there is symmetry about the diagonal which explains the diagonal values of 1.0000 since there is a perfect correlation of the variable with itself. The correlation matrix, therefore, shows a mixture of positive and negative relationships between the outcome variable and the predictors. It is imperative to note that of all the variables the correlation between LTRAV and BGS2 maintained the highest strength of relationship with a figure of 0.7020. While the values of other variables and the relationships they exhibit with other variables are shown in a pairwise form.

Figure 2 shows the trend in the variables used for our analysis. Notably, the graph indicates a decline in travel services and most measures of sentiment. This indicates valuable information content in sentiment for modelling travel services.

Figure 2. The trend of the variables



3.2 Model and Methods

3.2.1 Policy Simulations and an application of the Novel Dynamic ARDL Model

In this study, the function employed, which is the function of travel services, is expressed as:

$$TRAV = f\,(TRAD, RGDP, FDI, BCI)$$

$$TRAV = f\,(TRAD, RGDP, FDI, CCI)$$

$$TRAV = f\,(TRAD, RGDP, FDI, BBS)$$

$$TRAV = f\,(TRAD, RGDP, FDI, BGS1)$$

$$TRAV = f\,(TRAD, RGDP, FDI, BCI, CCI, BBS, BGS1)$$

The model for the Novel Dynamic ARDL simulation is expressed as:

$\mathrm{LTRAV} = \beta_0 \mathrm{LTRAV}_{t-2} + \ldots$

The novel dynamic ARDL simulation was employed to test for cointegration, long and short-run equilibrium relationships at both levels and differences. Also, there is the visualization interface advantage that the novel dynamic ARDL simulations provide especially when considering the counterfactual change that could result in the variable of choice based on the *ceteris paribus* assumption. Stationary test, in order to avoid a nonsensical outcome from the Novel Dynamic ARDL model, were initially carried out on the variables in the model. Augmented Dickey-Fuller (ADF) in conjunction with Phillips-Perron (PP) were the two-unit root test employed. The hypothesis of both test is existence of unit root in the null hypothesis with a stated condition. If rejected, then the series has no unit root and therefore is stationary, otherwise, it is non-stationary and needs to be first differenced.

4. Results and Discussion

The unit root test, as exposed in the table 4, was carried out on the logged values of the target variables. At levels, for the Phillips Perron (PP) tests, LTRAV, LTRAD, LRGDP and LFDI are non-stationary. Similarly, at levels, the result of the Augmented Dickey-Fuller (ADF) tests indicate that five variables LTRAV, LTRAD, LRGDP, LFDI and CCI were non-stationary.

Table 4: Stationary test

Variable	Level. PP	Δ. PP	Level.ADF	Δ. ADF
LTRAV	0.592	-0.937	0.909	-1.253
LTRAD	-2.052	-5.536	-2.054	-5.549***
LRGDP	-1.766	-2.997**	-1.905	-3.084**
LFDI	-2.493	-5.672***	-2.412	-5.640***
CCI	-2.571*	-5.334***	-2.512	-5.370***
BBS	-3.058**	-7.202***	-3.009**	-6.540***

Level.PP is the level of PP unit root, Δ. PP is the first-difference value; Level.ADF level of ADF, Δ. ADF is the first difference; ***, **, * significance at 10%, 5%, and 1% respectively

The presence of unit root at levels stemmed from accepting the null hypothesis and was sufficient reason for the variables to be differenced once more. After the first difference, it was confirmed that the variables are stationary, and hence integration of I(1). This make ARDL model the suitable model for the estimation. Furthermore, the optimal lag for the ARDL (1,0,0,1,0,1) regression (Table 4) is estimated. The estimation – long-run and short-turn – are either with/without sentiment proxies.

4.1 ARDL Model Estimation.

Table 5 below shows the different variants of the model with one or more variables being simulated to have a more robust study. The more encompassing model, as revealed in table 1, is the full model with all sentiment measures. The result denoted that, for the model with CCI, while LTRAD is nonsignificant, GDP per capita; foreign direct investment and CCI are significantly determine Travel Services (LTRAV) in the short-run estimation as well as and long-run estimation.

Table 5. ARDL (1,0,0,1,0,1) regression

	The model with only CCI	The model with CCI and BCI	The model with CCI, BCI, and BBS	Model without BBS	Full Model with all sentiment measures
VARIABLES	ADJ	ADJ	ADJ	ADJ	ADJ

ECT	0.773***	0.327*	0.313*	0.327*	0.319*
	(0.199)	(0.165)	(0.172)	(0.169)	(0.174)
Long run					
LTRAD	0.427	-1.858**	-1.866**	-1.853**	-1.847**
	(0.479)	(0.738)	(0.849)	(0.755)	(0.790)
LRGDP	-1.284***	0.868***	0.879***	0.867***	0.865***
	(0.417)	(0.216)	(0.254)	(0.221)	(0.231)
LFDI	-0.145*	-0.0486	-0.140	-0.0506	-0.0564
	(0.0707)	(0.176)	(0.209)	(0.183)	(0.193)
CCI	0.160***	-0.153	-0.154	-0.154	-0.150
	(0.0320)	(0.114)	(0.114)	(0.117)	(0.121)
BCI		0.0821	0.0560	0.0823	0.0903
		(0.0756)	(0.0698)	(0.0771)	(0.0882)
BBS			1.744		-0.362
			(1.216)		(1.185)
BGS1				0.00633	0.0266
				(0.116)	(0.138)
Short Run					
Δ LTRAD	-0.330	0.607	0.583	0.607	0.589
	(0.375)	(0.379)	(0.358)	(0.386)	(0.397)
Δ LRGDP	9.373***	-0.284*	3.991*	-0.284*	-0.276
	(2.201)	(0.154)	(2.143)	(0.157)	(0.162)
Δ LFDI	0.112*	0.0159	-0.0827	0.0166	0.0180
	(0.0649)	(0.0573)	(0.0790)	(0.0597)	(0.0609)
Δ CCI	-0.0443*	0.0501**	0.0483*	0.0504**	0.0479**
	(0.0231)	(0.0198)	(0.0243)	(0.0207)	(0.0225)
Δ BCI		-0.0269*	-0.0175	-0.0270*	-0.0288
		(0.0153)	(0.0178)	(0.0157)	(0.0170)
Δ BBS			-0.545*		0.115
			(0.305)		(0.363)
Δ BGS1				-0.00207	-0.00849
				(0.0380)	(0.0436)
Observations	33	32	32	32	32
R-squared	0.647	0.474	0.591	0.474	0.476

Note: Standard errors in parentheses while *** p<0.01, ** p<0.05, * p<0.1 represents 1%, 5% and 10% statistical significance levels. Parameters estimates of the ARDL model. Legend: RGDP represents Real Gross Domestic Product; FDI represents foreign direct investments.

Under the model with CCI and BCI, LRGDP, CCI and BCI are significant only in the short-run while LTRAD and Real GDP remained significant in the long-run.

Under the model with CCI, BCI and BBS; Real GDP, CCI and BBS are significantly influence LTRAV in the short run while LTRAD and Real GDP were significant in the long run. Under the model without BBS, Real GDP, CCI and BCI are significantly influence LTRAV of LTRAV in the short run while LTRAD and Real GDP remained significant in the long run.

Finally, under the model that included all sentiment measures in the last column of Table 5, only CCI is a significant predictor of LTRAV while LTRAD and real GDP remained significant in the long run. Put together, our findings complement the work of Dragouni *et al.*, (2016), who find that sentiment and mood is an important determinant of outbound tourism. In contrast to their work, we demonstrate that sentiment significantly affects the inflow of revenue from travel services to the US economy. Results from Table 6 below, shows the model diagnostics of cointegration relationship by employing Shin, Pesaran and Smith (PSS) bound tests in conjunction with the Kripfganz and Schneider (KS) critical value.

Table 6. Model Diagnostics Tests

a. Pesaran, Shin, and Smith bounds testing

		10%		5%		1%		*p-value*	
	K	I (0)	I (1)	I (0)	I (1)	I (0)	I (1)	I (0)	I (1)
F	7.075	2.122	3.365	2.636	4.059	3.9	5.741	0.000**	0.003**
T	3.882	-1.613	-3.246	-1.98	-3.668	-2.72	-4.523	1.000	1.000

I (0) is the lower band critical values; I (1) is the upper band critical values; ** indicate the significance of KS critical values at the 0.01 significance level.

b. Breusch-Godfrey LM test for autocorrelation

lags(p)	F	Df	Prob > F
1	3.64	(1, 27)	0.0671
2	2.219	(2, 26)	0.1289
3	1.496	(3, 25)	0.24
4	1.291	(4, 24)	0.3013

c. **Cameron & Trivedi's decomposition of IM-test.**

Source	chi2	Df	*p-value*
Heteroskedasticity	33	32	0.418
Skewness	20.11	7	0.0053
Kurtosis	1.02	1	0.3115

Total	54.13	40	0.0671

d. Skewness/Kurtosis tests for normality

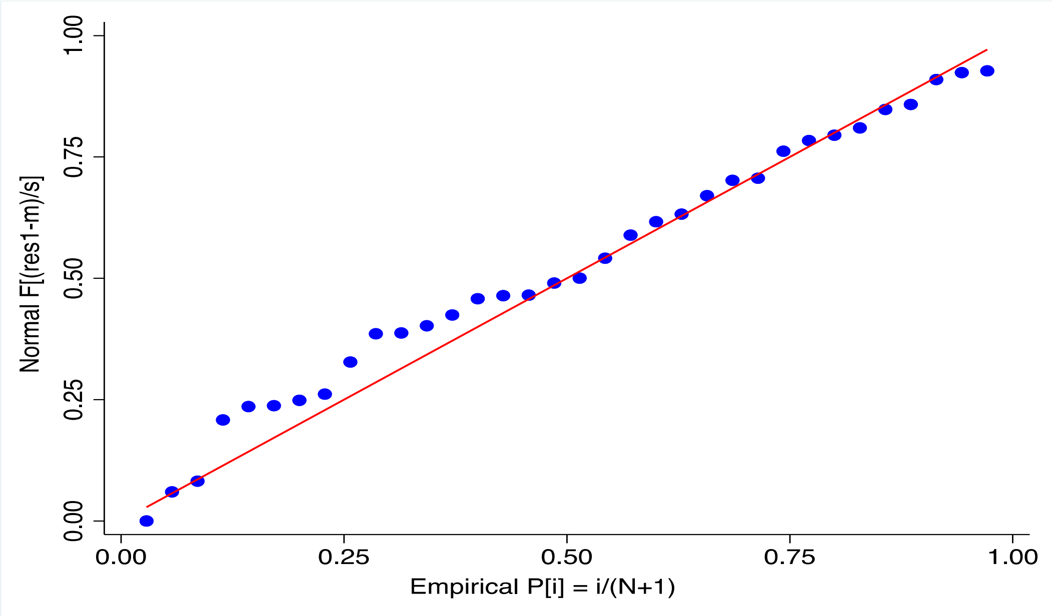
Variable	Obs.	Pr. (skewness)	Pr. (kurtosis)	Joint adj. chi^2(2)	Prob>chi2
Residuals	34	0.0656	0.4121	4.22	0.1212

Table 6a reveals that the combined F-statistic of the parameter estimates (short-run coefficients) is 7.075, while the absolute value of t is 3.882, both of which are more than the upper bound, I (1), critical values at 10% and 5% significance levels. The KS level of significance (p-value< 0.01) adds credibility to the finding, resulting to the assertion of no cointegration in H0 and its dismissal. As a result, both experiments proved the presence of long-run cointegration.

Several tests were performed to internal validity of the assumption of the dynamic ARDL, including checks for serial correlation, heteroscedasticity, autocorrelation and violation of the normality assumption, and structural breaks. Table 6b displays the autocorrelation test using the Breusch-Godfrey LM serial correlation test. As the p-value is larger than 0.05, the hypothesis of no serial correlation between variables and their lagged values is refuted at a 5% level of statistical significance. Based on the results in 4b, we may conclude that the residual of the computed ARDL (1,0,0,1,0,1) is devoid of autocorrelation. Cameron and Trivedi's decomposition of the IM-test, illustrated in Table 6c, investigated residual heteroscedasticity. The p-value is greater than 0.05, indicating that H0 as a null hypothesis is fail to reject, and so the residuals are homoscedastic. Additionally, employing the skewness and kurtosis tests, the normality assumption of independence among the residuals was observed, as shown in Table 6c. Table 6d reports the degree to which the residuals followed the normality assumption and the H_0 is also accepted in this case at the 0.05 level of significance. Hence, we can confidently state that the residuals are normally distributed.

4.2 ARDL Regression: Post-estimation diagnostics.

The validity of the normality assumption as revealed by the skewness/kurtosis test was again checked using the standardized normal probability plot (shown in Fig. 4) and the quantiles of residuals versus the normal distribution quantiles (shown in Fig. 5). Based on ARDL(1,0,0,1,0,1), both graphs detect the presence of regularly dispersed residuals.



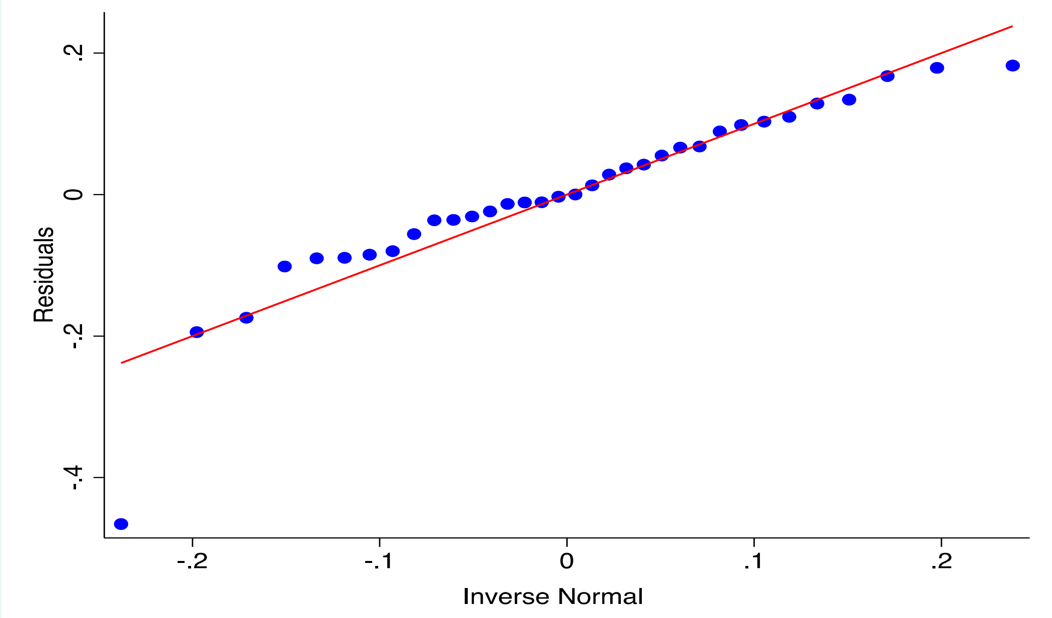
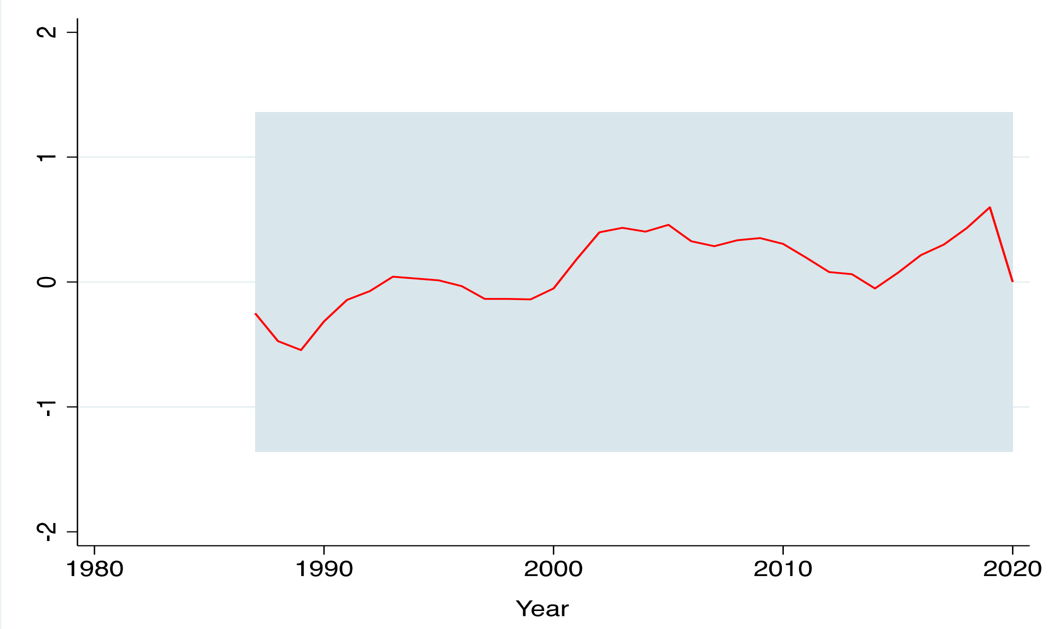


Figure 5. Quantiles of residuals against quantiles of normal distribution

The results of the cumulative sum tests utilizing the OLS CUSUM plot revealed that there was a structural break. The result shown in Fig. 6 implies that the calculated parameters' test statistic is within a 95 percent confidence range. As a result, we may accept the predicted coefficients of the parameters' stability across the time period in question.



OLS CUSUM plot of LTRAD with 95% confidence bands around the null

Figure 6. Cumulative sum test using OLS CUSUM plot for parameter stability

5. Investor Sentiments Policy Simulations

5.1 Dynamic ARDL Simulations

The simulation of the dynamic ARDL as it pertains to this study is based on +26% economic growth for over 20years, 2019-2039. The parameter plot of the dynamic ARDL is presented in Fig. 3 while its empirical estimation is in Table 5.

The model with CCI indicates CCI and Real GDP significantly predicts travel services in the short and long run. It is important to note that CCI was negatively signed against Travel services indicating a negative relationship between CCI and travel services. In effect, an increase in CCI will result in a decrease in Travel Services.

The model with BCI shows a different analysis as real GDP is the only variable that significantly predicts travel services in the short run. However, the relationship here remained positive as reported for the previous model; all pointing to the fact that increased travel services will increase economic production. The model using BBS demonstrates that Real GDP strongly predicts travel services in both the short and long run, but BBS predicts travel services mainly in the long run. Only in the short term does Real GDP strongly predict travel services in the final model with BGS as the focal point.

The model with CCI had the highest r-squared value of 0.669 of all the models presented in Table 5, implying that the explanatory variables can account for 66.9 percent of the variability in travel services, emphasizing this model as the only model that stringed two variables that significantly predicted travel services. The model that comes second in r-squared value is the model with BBS, with a value of 0.555 implying that 55.5% of the variability in travel services is explained by the predictors. The other models had lesser r-squared values; with values of 0.452 and 0.436 for models with BCU and BGS respectively.

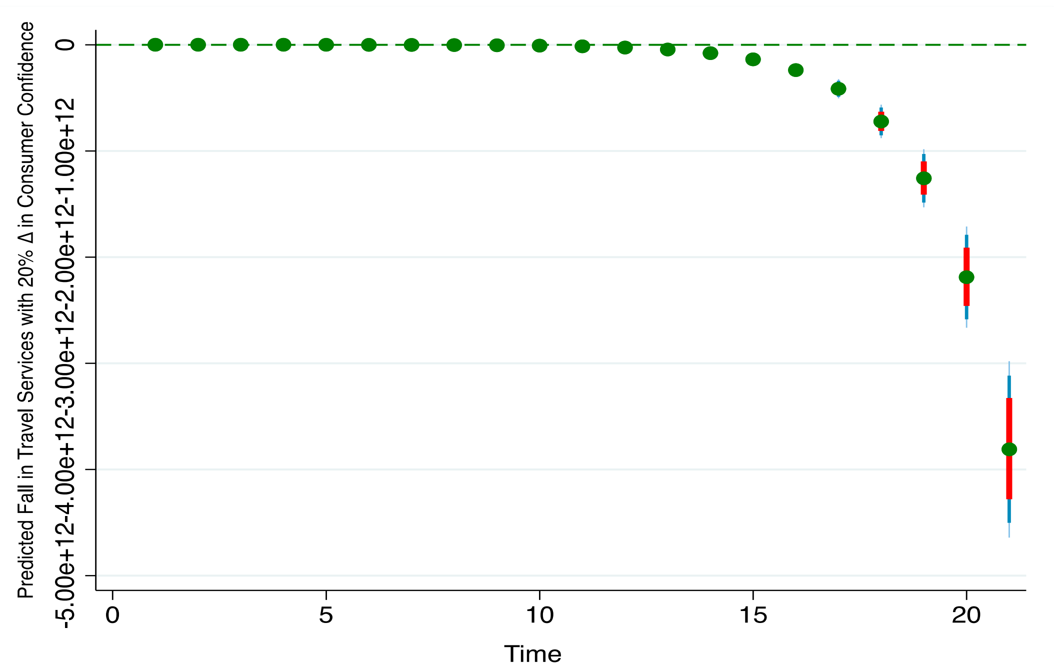
Generally, both ARDL and dynARDL estimates depict those policies that encourage trade, foreign direct investment, will increase the economic returns to the travel services sector which would cause a positive ripple effect on the tourism sector of the U.S. economy. Then, using the dynARDL estimator, we examine the impacts of declining marginal returns of BBS and CCI on Travel Services as a result of a +26 percent shock in BBS and CCI, with a 20-year window for a guesstimated gestation time, i.e., 2019 and 2039. The dynARDL simulations plots are shown in panels a and b of figure 8. The simulation in Panel a show that +26% shock in the estimated CCI & BBS on economic growth increased over a larger part of the period in view but decelerates afterwards, as we approach the first period of 2028. The simulation in Panel a show that +26% shock in the estimated CCI & BBS on Travel services increased over a larger part of the period in view but decelerates afterwards, as we approach the first period of 2028. Both plots showed that travel services will ultimately decrease in the long run. The results contrast with the view that the effect of sentiment on tourism will wane in long run (Dragouni *et al.*, 2016).

Table 7. Estimates of dynamic simulated ARDL model.

	The dynamic model with CCI	The dynamic model with BCI	The dynamic model with BBS	The dynamic model with BGS
VARIABLES	dLTRAV	dLTRAV	dLTRAV	dLTRAV
LTRAV $_{t-2}$	0.739***	0.143	0.217	0.125
	(0.194)	(0.164)	(0.151)	(0.242)
CCI $_{t-2}$	-0.108***			
	(0.0258)			
LTRAD $_{t-2}$	-0.138	0.468	0.539*	0.508
	(0.300)	(0.379)	(0.290)	(0.348)
LRGDP $_{t-2}$	0.795***	-0.0930	-0.234*	-0.198
	(0.254)	(0.412)	(0.121)	(0.161)
LFDI $_{t-2}$	0.118*	-0.0643	0.00909	-0.0415
	(0.0669)	(0.0802)	(0.0605)	(0.0681)
BCI $_{t-2}$		-0.0106		
		(0.0360)		
BBS $_{t-2}$			-0.870**	
			(0.341)	
BGS $_{t-2}$				0.00719
				(0.0693)
Δ LRGDP	8.918***	6.153**	8.245***	5.836***
	(1.731)	(2.407)	(1.766)	(1.721)
Δ LFDI	0.0303	-0.141	-0.105	-0.121
	(0.0749)	(0.0851)	(0.0725)	(0.0829)
Δ CCI	-0.0340*			
	(0.0201)			
Δ BCI		-0.0177		
		(0.0199)		
Δ BBS			-0.254	
			(0.281)	
Δ BGS				0.0246
				(0.0514)
Observations	33	33	33	33
R-squared	0.669	0.452	0.555	0.436

Note: Standard errors in parentheses while *** p<0.01, ** p<0.05, * p<0.1 represents 1%, 5% and 10% statistical significance levels. Parameters estimates of the ARDL model.

Panel A



Panel B

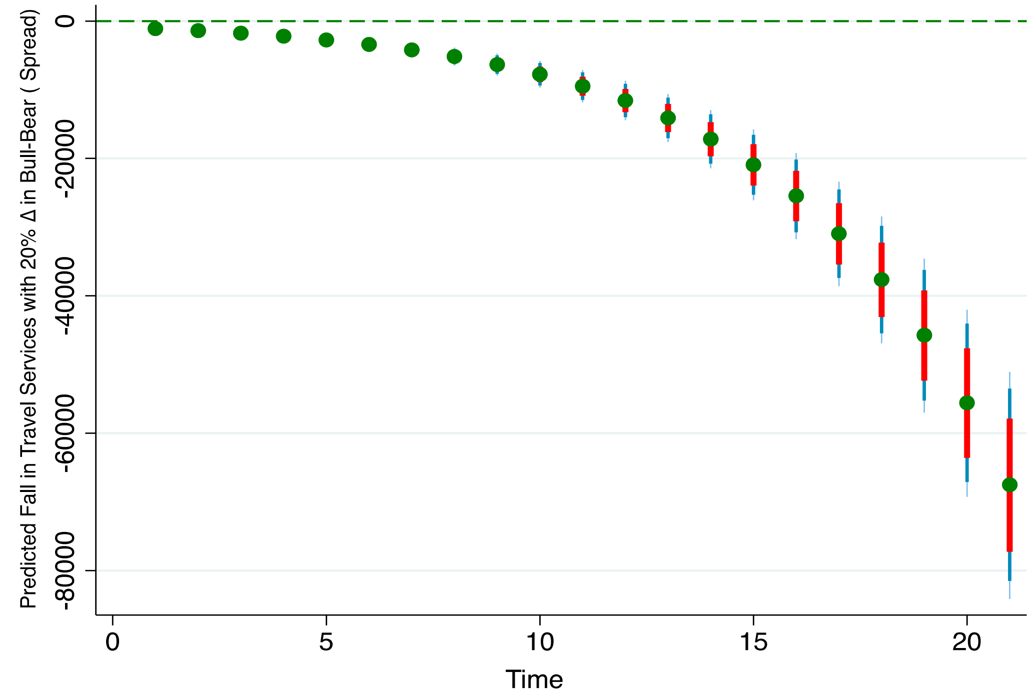
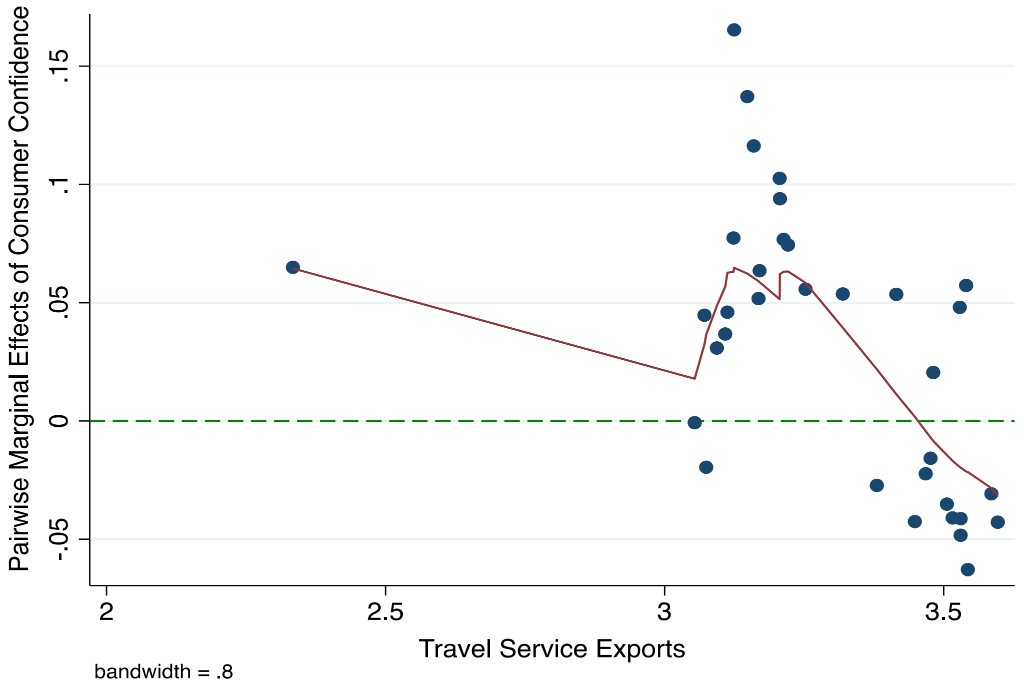


Fig. 8. Counterfactual shock in predicted CCI & BBS using dynamic ARDL simulations. *Notes:* black (x) is the predicted Travel Services by a +26% shock in consumer confidence and bull-bear spread (BBS); olive teal, red and green spikes denote 75, 90, and 95% confidence interval. Year 0 represent 2019 and 20 represent 2039 with a five-year interval.

Panel A



Panel B

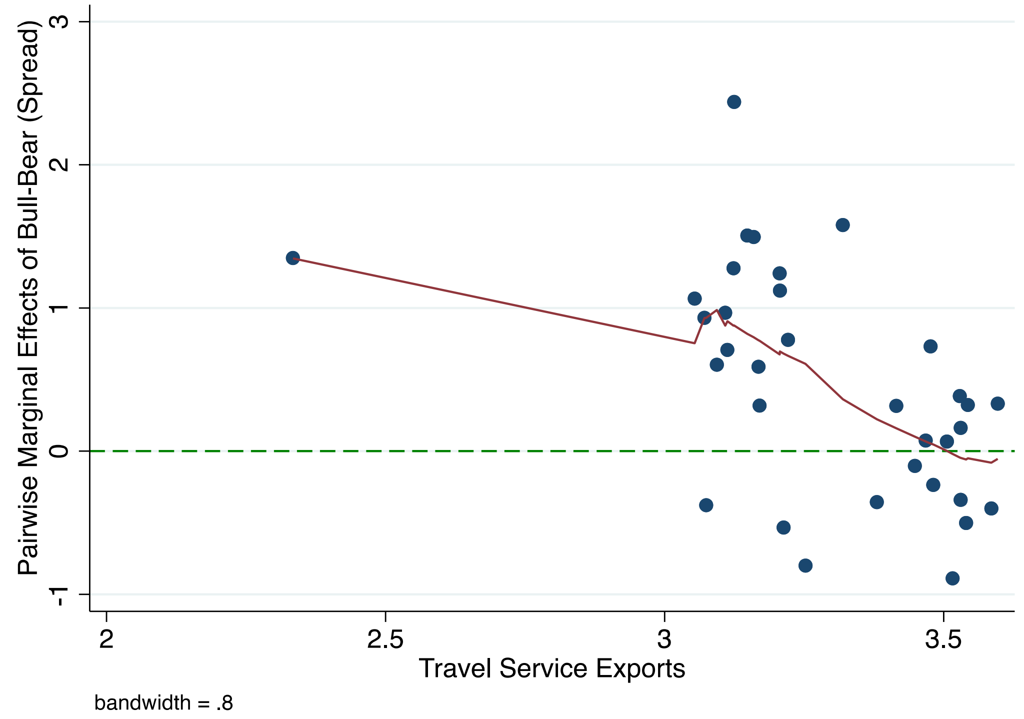
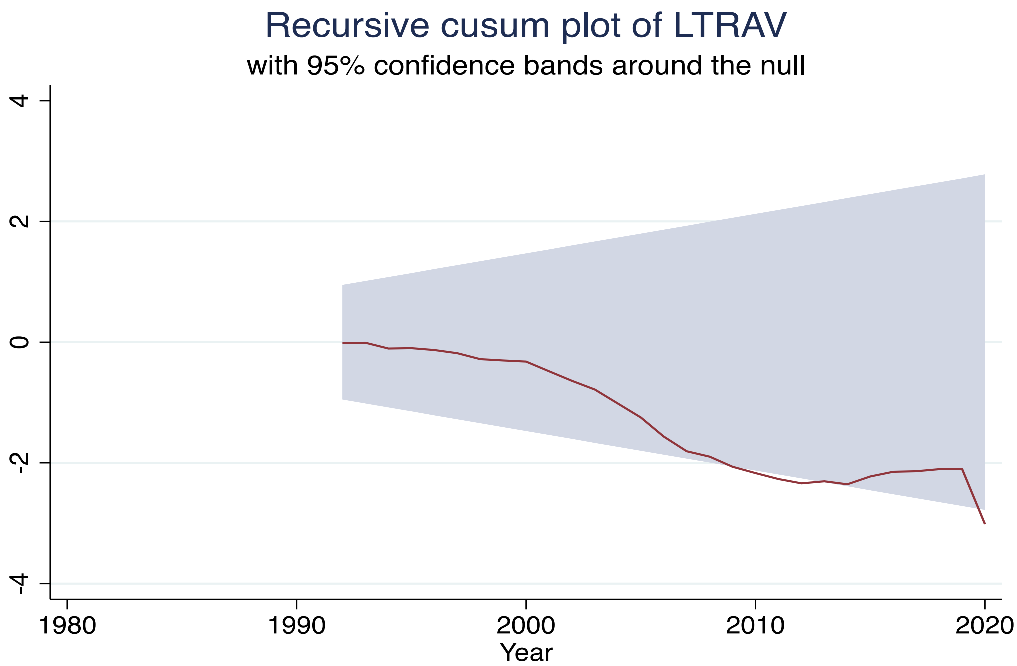
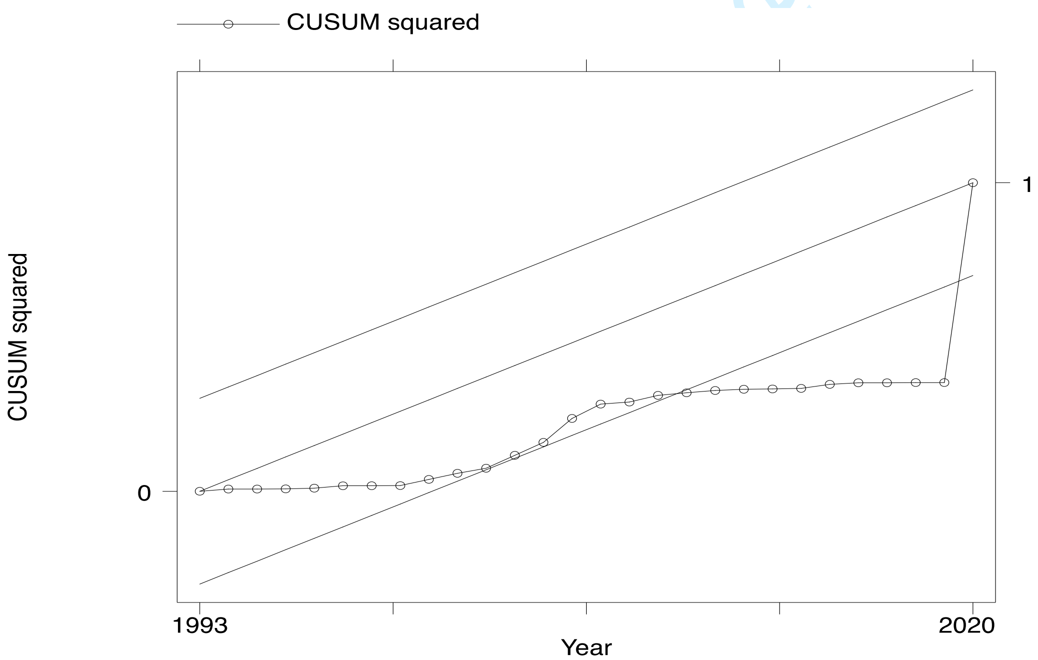


Figure 9. Representation of Pointwise marginal effect of CCI and BBS

5.2 Simulated Shocks to Business and Investor Sentiments in the USA

The CUSUM and CUSUM squared plots are used to examine the structural stability of the long-run variables in combination, as seen in the figure below. As a rule of thumb, if the plots of the CUSUM and CUSUMSQ statistics remain within the critical or confidence bands at a 5% level of significance, the null hypothesis of all coefficients in the regression cannot be rejected since they are stable. The Recursive CUSUM and CUSUMSQ plots in the figure below demonstrate that the statistics are substantially inside the 5% critical constraints, demonstrating that the short and long-run coefficients in the ARDL-Error Correction Model are stable.





6. Conclusion and Policy Implications

In this study, using forward-looking models, we analyze the interplay between sentiments and travel services and consider a simulation of the post-COVID-19 era. We examine the linkages between changes in unique measures of sentiment and travel services over the period of 2019–2039. The study represents a bold response to providing empirical evidence on travel services in the post-COVID-19 pandemic era.

To examine our hypothesis, we use the innovative dynamic autoregressive distributed lag model (dynARDL). We present various simulations of variable inclusion or exclusion to ensure robust estimates. The study takes into consideration the influence of trade, real GDP, and foreign direct investment on travel services. We also study short- and long-term relationships utilizing ARDL, new dynARDL, and sentiment metrics as they relate to international travel.

According to the findings, both ARDL and dynARDL models demonstrate a substantial long-term link between travel services and various factors such as real GDP, trade, and various sentiment measures. More specifically, under the model that included all sentiment measures, Consumer Confidence Index (CCI) was the only significant predictor of travel services while trade and real GDP were significant in the long run. This finding further necessitates policies addressing the adverse impact of business sentiments to travel service exports in the USA.

In conclusion, our findings from recent data and model specifications defined by this study show that both ARDL and dynARDL estimates depict that policy interventions could encourage trade and foreign direct investment in the United States, thereby increasing economic returns to the travel services sector. This will inevitably cause a positive ripple effect on the tourism sector of the U.S. economy. Similarly, the forecasting model predicts a decline in travel in the future, for tourism-dependent countries this further strengthens the argument for economic diversification. Finally, when forecasting travel inflows, tourism policymakers should consider the role of investor sentiment (in the short run) and CCI (in the long run).

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