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Explaining US travel behavior with perceived threat of pandemic, consumer sentiment, and economic policy uncertainty

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ABSTRACT

Since the COVID-19 outbreak, consumer behavior has been affected by the perceived threat of the pandemic and economic uncertainty. This paper aims to explore the dynamic effects of COVID-19, consumer sentiment, economic policy uncertainty, and fuel prices on travel behavior in the United States. Using updated daily trip data, the results show that consumer sentiment has a positive long-run impact on travel demand for air and auto, suggesting that a positive change in consumer sentiment can boost demand for these modes of transportation in the long term. Additionally, consumer sentiment has a favorable effect (1.34) on demand for long-distance trips, but it has a negative impact (−0.42) on the number of people staying at home. Economic and political shocks have a detrimental impact on demand for air and auto travel, suggesting that consumers reduce the frequency and cost of these transport services if they have pessimistic expectations about the future state of the economy and policy. However, in the short term, US travelers appear to be insensitive to shocks in consumer sentiment and economic policy uncertainty. Regarding the perceived threat of the pandemic, the results indicate that rising COVID-19 cases have a negative long-term effect on demand for air travel (−0.09) and public transit (−0.19), while they are positively associated with demand for auto travel (0.06). Similarly, the increasing number of deaths due to COVID-19 has led to a shift from shared-use mass transportation (air travel and public transit) to private autos and non-motorized travel, such as walking in the short term.

1. Introduction

Given the vital role of the travel industry in supporting sustainable mobility and economic development, the assessment of the factors affecting travel behavior has long been an important topic for researchers and policymakers. A considerable number of studies have focused on determining the factors that influence travel demand at a national level. In models examining aggregate travel demand, macroeconomic indicators such as gross domestic product (GDP), various income measures at the individual, household, or national levels, and transportation costs, have been commonly used as explanatory variables (e.g., Goodwin et al., 2004; Alam et al., 2018; Fouquet, 2012; Graham and Glaister, 2004; Gallet and Doucouliagos, 2014; Le Vine et al., 2014).

Since the COVID-19 outbreak, there has been a surge in research on the impact of the epidemic on travel behavior (e.g., Gössling et al., 2020; Bucsky, 2020; Nižetić, 2020; Lau et al., 2020; Truong, 2021; Manca et al., 2021; Yilmazkuday, 2021; Kopsidas et al., 2021). For example, Bucsky (2020) reported that one of the key policy responses to the COVID-19 pandemic has been restrictions on movement of people. His study also showed that the extent of reduced mobility differs by mode of transportation, with public transportation services experiencing the largest decrease in demand. Nižetić (2020) examined the effect of COVID-19 on air transportation mobility and discovered that the number of flights declined by over 89% in the European Union. Kopsidas et al. (2021) explored the anticipated post-pandemic behavior of travelers using public transportation. Based on the case of Athens, Greece, they found evidence that self-employed individuals and personal-vehicle users are unlikely to use public transportation during the pandemic period.

Although the impact of macroeconomic factors and COVID-19 on transportation demand has been well documented in the literature, there has been limited attention given to factors beyond macroeconomic data, such as consumer sentiment regarding the economic outlook and policy uncertainty. Consumer sentiment refers to consumers' beliefs about current economic and financial situations and their expectations for the future (Jin et al., 2022). The COVID-19 crisis has had a profound effect on consumer behavior, and uncertainties about the economic downturn and recovery from COVID-19 have influenced fiscal, monetary, and

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other regulatory policies. In the aftermath of the COVID-19 crisis, travel demand may be highly sensitive to consumer confidence and economic policy uncertainty. However, there is limited information on the effect of consumer sentiment and economic policy uncertainty on individual mobility and travel behavior.

In the fields of economics and tourism, there has been a growing interest in consumer sentiment and economic policy uncertainty. Consumer sentiment has been used to explain consumer buying behavior (Malgarini and Margani, 2007), household financial behavior (Białowolski, 2019), and financial and stock market changes (Al-Thaqeb and Algharabali, 2019; Hadood and Irani, 2020). In the tourism industry, consumer sentiment and economic uncertainty have been identified as important factors in determining tourism demand (Dragouni et al., 2016; Jin et al., 2022). For example, Dragouni et al. (2016) analyzed the impact of consumer sentiment, economic policy uncertainty, and the S&P 500 on outbound tourism demand using indexes of these factors. Their findings showed the existence of spillover effects of shocks to sentiment and mood on tourism demand, but these effects are event and time dependent. Jin et al. (2022) investigated the factors that affect consumers' travel demand and decision-making, and found that the COVID-19 pandemic has resulted in health threats, economic concerns, and travel restrictions, leading to a larger negative effect on travel behavior than previous crises.

This study aims to address the following issues. First, this study explores the role of consumer sentiment and economic policy uncertainty in travel behavior in the post-COVID-19 era. With the recent pandemic-related economic downturn, it is timely and essential to determine if consumer sentiment and economic uncertainty can influence travelers' behaviors and transportation mode choices. According to Marsden and Docherty (2021), the transport industry was largely unprepared for the COVID-19 crisis, and decision makers should consider how consumers would alter their travel behaviors to fit the new normal.

Sociocultural, psychosocial, and social cognitive factors can influence transport mode choice. Raude et al. (2020) discovered that self-reported adoption of preventive behaviors in response to COVID-19 was significantly associated with the level of trust in government. Incorporating sociocognitive variables, such as perceived susceptibility and severity, was also found to improve the explanatory power of the hierarchical regression model, suggesting that sociocognitive aspects are crucial in the adoption of preventive health practices. Al-Rashid et al. (2021) examined the effects of the health and psychosocial characteristics influencing the mobility on the intention on public transit use. Their findings indicated a positive association between attitudes and public transit use intentions, suggesting that positive perceptions and attitudes increase intentions to use public transit. Motivated by this body of research, this study investigates the impacts of consumer sentiment and economic policy uncertainty on travel behavior to provide implications for post-pandemic strategies and policy plans. Consumer confidence shocks caused by the COVID-19 crisis may decrease demand for travel and tourism, particularly for air and car travel. Understanding modal shifts between transport modes during a pandemic situation can provide important information for managing the pandemic and its consequences. Additionally, this information can aid policymakers in predicting transport use, mobility, and travel behavior in the post-pandemic period.

Second, this study assesses the real-time effects of consumer sentiment and economic uncertainty on travel behavior. Previous investigations have often utilized macroeconomic indicators, which are typically available on a monthly or quarterly basis. This approach limits their usefulness in capturing the dynamic effects of daily lags and supporting a more resilient transport policy, particularly when pandemic and uncertainty shocks can hit with great suddenness. Truong and Truong (2021) found that US travel behavior changed daily in response to travelers' perceptions of the COVID-19 pandemic risk. Hence, it is crucial to compare the short- and long-term impacts of sentiment and uncertainty shocks on travel demand. By analyzing both short- and long-term effects, we can gain insight into the modal shifts during the pandemic and potential long-term changes in travel behaviors post-COVID-19. The application of a dynamic method using daily data can offer valuable information about the near-term effects of travel demand determinants, guiding short- and medium-term policy options.

To tackle these issues, this study employs the autoregressive distributed lag (ARDL) to analyze both short-term dynamics and long-term parameters. Using daily data from the United States (US), we explore the dynamic effects of COVID-19, consumer sentiment, economic policy uncertainty, and oil prices on transport mode preferences (air, auto, public transit, and walking modes) and trip distances (short-, medium-, and long-distance trips). To the best of our knowledge, this is the first study to examine both short- and long-run impacts of sentiment and uncertainty shocks on travel behavior. The ARDL approach has distinctive advantages over other cointegration techniques. First, the short- and long-run coefficients can be estimated simultaneously through an error correction model (ECM). Second, the ARDL mehod can be applicable regardless of whether the variables are entirely $I(0)$, entirely $I(1)$, or fractionally integrated. Additionally, this approach performs better than other cointegration methods, such as the Engle–-Granger and the Johansen techniques, when dealing with small- or finite-sample data sizes (Pesaran and Shin, 1999).

The remainder of the paper is structured as follows. The following section provides a selective literature review of government responses to the COVID-19 crisis, travel behavior changes, and consumer sentiment and economic policy uncertainty. The third section presents a discussion of the protection motivation theory. The data used in this study are then described in the fourth section. The fifth section discusses the ARDL model, and the sixth section reports empirical findings. This paper concludes with a summary of the main findings, policy implications, and limitations of the present study.

2. Literature review

2.1. Government's responses to COVID-19 pandemic

The outbreak of COVID-19 has caused unprecedented disruptions to mobility. During the early stages of the pandemic, the effectiveness of government responses to COVID-19 has been investigated. According to Dergiades et al. (2022), early and strong government interventions were more effective in reducing the growth rate of COVID-19 deaths. Vinceti et al. (2020) found that less stringent lockdowns were not effective in reducing mobility enough to control the spread of COVID-19, leading to the conclusion that a stronger lockdown was necessary. Olney et al. (2021) explored the effects of various social distancing interventions in the US before and after the implementation of lockdowns. Their study found that only school closures and lockdowns appear to have a significant role in reducing COVID-19 reproduction cases. Guo et al. (2021) analyzed the linkage between COVID-19 and travel-related factors, such as social distancing index, residents staying at home, and travel frequency and distance. Using data from Honolulu county, the results showed a significant correlation between social distancing measures and COVID-19 cases.

According to Meng et al. (2021), stricter COVID-19 control measures would have a more pronounced short-term effect on the air transport industry, but their long-run effect would be relatively insignificant. However, other studies have produced mixed results regarding the impact of travel restrictions and testing strategies on COVID-19 transmission. For example, a systematic review of 34 empirical studies conducted by Mendez-Brito et al. (2021) found that public transport closure, testing strategies, contact tracing strategies, and quarantining did not have significant evidence of being effective against COVID-19. Similarly, Courtemanche et al. (2020) found that school closures and large event bans did not significantly affect the growth rate of COVID-19 cases across US counties. Bian et al. (2021) studied the time lag effects of COVID-19 policies on transportation systems in New York and Seattle and found a lead effect of stay-at-home and reopening policies on mobility, but no significant evidence of a lag effect from the national declaration of emergency. Given the mixed findings in the existing literature, it is necessary to revisit the impact of COVID-19-related lockdowns and stay-at-home orders.

2.2. *Travel behavior changes during the COVID-19 pandemic*

There has been growing attention in the academic literature to the effect of COVID-19 on travel behavior (e.g., Gössling et al., 2020; Abdullah et al., 2020; Yilmazkuday, 2021; Bucsky, 2020; Truong and Truong, 2021). For instance, Gössling et al. (2020) conducted a survey to assess the impact of the COVID-19 epidemic on daily mobility in Poland. The results indicated that respondents significantly reduced their travel times, with this trend being consistent across all age and gender groups. Abdullah et al. (2020) used an online questionnaire survey to examine the effect of COVID-19 on travel behavior. Their results showed that COVID-19 has significantly affected travel mode, trip distance, and frequency. Car ownership, gender, employment level, trip distance, and infection-related factors (e.g., social distancing) were found to have a significant impact on transportation mode choice. Using the autoregressive integrated moving average (ARIMA) model, Truong and Truong (2021) analyzed the relationship between the COVID-19 pandemic and daily trips in the US. The results showed a strong correlation between daily COVID-19 cases and deaths and the distance traveled by individuals. Their analysis also revealed that travelers' behavior, including the frequency of trips and travel distance, changed dynamically based on their perceived risk of COVID-19.

A group of studies has focused on the effects of COVID-19 on specific modes of transportation. For example, Truong (2021), Manca et al. (2021), and Lau et al. (2020) studied the relationship between the COVID-19 crisis and air travel demand. Truong (2021) used a neural network model and Monte Carlo simulation to examine the effect of COVID-19 on domestic and international travel in the medium and long term. The results indicated that air travel demand is more sensitive to changes in the weekly economic index (WEI) than it is to the severity of COVID-19. He also suggested that it would take at least a few years to fully recover air travel demand in all-case scenarios. Lau et al. (2020) investigated the linkage between domestic air traffic and COVID-19 cases in China and found a significant relationship between COVID-19 cases and domestic air travel prior to the implementation of the lockdown. However, the correlation between COVID-19 outbreaks and air travel demand became weaker after the lockdown period. Additionally, Gallego and Font (2021) analyzed Skyscanner data on air travel searches and found that the desire to travel, as measured by the number of flight searches, declined by approximately 30% in the Americas. The intention to travel, as measured by the number of selected flights among flight searches, decreased by an additional 10 or 20%.

Regarding the effect of COVID-19 on public transportation, Wielechowski et al. (2020) found a significant negative correlation between the severity of anti-COVID-19 policies and mobility changes in public transport in Poland. However, there was limited evidence of a negative relationship between epidemic status and mobility changes. Aparicio et al. (2021) used passenger trip data for three options of public transportation (subway, bus, and tramways) to study the socioeconomic disparities of users across different metropolitan areas. The results showed a weak relationship between COVID-19 and transit ridership with lower income levels outside of the Lisbon municipality. Abdullah et al. (2021) investigated the effect of COVID-19 on transport mode choices in Pakistan using an online questionnaire. Their findings indicated significant changes in travel behavior, with a shift from motorbike to non-motorized modes for short-distance trips and from public transport to personal vehicles for longer trips.

Similarly, Ku et al. (2021) explored the effect of COVID-19 on travel behavior during the first half of 2020. Based on passenger occupancy rates, they observed a decline in the usage of bus and rail services, while the use of personal vehicles and public bicycles had either fully recovered or increased when compared to pre-pandemic rates. De Vos (2020) discussed the implications of social distancing on daily travel behavior. The spread of the COVID-19 was found to reduce travel demand, particularly for public transport, resulting in social isolation and decreased physical activity. The results suggested that private travel options, such as walking and biking, could be crucial for maintaining health and well-being. The existing literature provides limited information on the dynamic impacts of COVID-19 on transportation mode preferences (e.g., air travel, driving, public transit, and walking) and trip distances (e.g., short, medium, and long-distance trips). To make informed post-pandemic policy decisions, it is essential to examine both the short- and long-term effects of COVID-19 on travel demand. The application of dynamic models based on daily data can provide valuable insights into the near-term effects of COVID-19 on travel demand.

2.3. *Consumer sentiment and economic policy uncertainty*

Given the high level of uncertainty experienced in recent decades, numerous studies have investigated the impacts of consumer sentiment and economic uncertainty on consumer behavior (e.g., Malgarini and Margani, 2007; Mian et al., 2015; Gozgor and Ongan, 2017; Demir and Ersan, 2017, 2018; Demir and Gözgör, 2018; Madanoglu and Ozdemir, 2019). Huth et al. (1994) proposed that consumer sentiment and confidence indices are valuable indicators for predicting aggregate consumer spending and economic activity. In the economic literature, consumer sentiment and confidence are often utilized to examine household behavior changes. For instance, Malgarini and Margani (2007) studied the effect of consumer sentiment on the consumption patterns of Italian households. Their study revealed that consumer sentiment plays a significant role in shaping their purchasing decisions, particularly with regards to travel and leisure spending. Regarding the role of economic sentiment in household financial behavior, Białowolski (2019) found that rising consumer confidence leads to an increase in debt for durable goods and mortgages but a decrease in debt taken out for consumption purposes.

Regarding economic policy uncertainty, Mian et al. (2015) examined the impact of changes in consumer sentiment towards government policy on consumer spending. They found weak evidence that sentiment shocks related to policy affect aggregate consumer spending. Al-Thaqeb and Algharabali (2019) reviewed the literature regarding the effects of policy uncertainty on financial and stock markets, consumer and corporate behavior, and risk management. Their study discovered that uncertainty shocks have a negative impact on consumer spending and corporate behaviors, such as investments in production and employment. Using firm-level data from BRIC countries, Demir and Ersan (2017) found a significant association between economic policy uncertainty and cash holdings. Their results showed that a 10-point increase in uncertainty leads to a 0.8% increase in the cash holdings ratio.

In the tourism industry, recent research has focused on the impact of economic sentiment and policy uncertainty on consumer behavior (e.g., Dragouni et al., 2016; Demir and Ersan, 2017; Hadood and Irani, 2020; Jin et al., 2022; Gholipour et al., 2022). For example, Dragouni et al. (2016) considered spillover effects from sentiment and mood shocks on tourism demand and found a significant linkage between sentiment, mood and outbound tourism demand in the US. The spillover effects varied considerably during times of environmental socio-economic shocks. Using panel data from African countries, Gholipour et al. (2022) investigated the impacts of consumer confidence and economic policy uncertainty on tourist flows to Africa. The results showed that increasing consumer confidence has a positive effect on tourism demand, while rising uncertainty has a negative effect on tourism demand.

Hadood and Irani (2020) investigated the impact of regional and European economic sentiment on travel and leisure stock returns. Their findings showed a significant positive correlation between regional economic sentiment and stock returns in France and Spain. In the short run, an increase in European economic sentiment led to positive stock returns in Spain and the UK. Demir and Ersan (2018) evaluated the impact of economic policy uncertainty on the stock prices of tourism firms in Turkey. The results indicated that domestic and European uncertainty shocks had a significant adverse effect on the returns of the tourism index, suggesting that the stock returns of tourism firms are influenced by both domestic and international economic uncertainty. Using data from travel and leisure sector stock returns, Zargar and Kumar (2021) also discovered the presence of directional spillover from consumer sentiment, mood, fear, and economic policy uncertainty to tourism sector returns in the US.

3. Protection motivation theory to understand travel behavior and modal preferences

According to Cox (1967), consumer's perceived risk is a function of uncertainty and consequences. During the COVID-19 pandemic, travelers may experience risks related to 1) the threat of pandemic (e.g., rising COVID-19 cases and deaths); 2) safety at their destination and mode of transportation; 3) degree of economic and financial prospects; and 4) political uncertainty. These risk factors can result in either positive or negative economic sentiment, based on the consumer's beliefs and attitudes towards the perceived risk. Consumers' spending and travel behavior may be affected by the uncertainty re surrounding the government's response to COVID-19 and the economic disruption. For instance, risk-averse consumers may reduce the frequency and cost of air travel if they have a pessimistic outlook on the state of the economy and policy. The protection motivation theory (PMT) suggests that travelers' behavior can be affected their perception of safety and risk at the destination (Wong and Yeh, 2009; Dillette et al., 2021; Ivanova et al., 2021). Although health-related risk perceptions may vary among individuals, it is widely acknowledged that it has a significant impact on travel destination choices (Reisinger and Mavondo, 2005). For instance, Ivanova et al. (2021) found that a destination's sanitation, disinfection, and availability of a reliable healthcare system can greatly influence travelers' decisions.

The PMT proposes that consumers evaluate information about perceived risks through two cognitive processes. Threat appraisal, the first component of PMT, involves the perception of severity and vulnerability to the threat and the perceived rewards (Rogers, 1975). For example, people's risk perceptions regarding COVID-19 may change over time, depending on the daily patterns of confirmed COVID-19 cases and deaths. Coping appraisal, the second component of PMT, evaluates people's abilities to cope with and avoid the threatened danger (Ch'ng and Glendon, 2014). Based on their perception of the severity of the pandemic, travelers may engage in protective behaviors, such as avoiding long-distance trips or shifting from shared public transportation to private vehicles. The PMT has been widely used to describe the cognitive processes that lead to behavioral adjustments when a risk factor exists (Rogers, 1975). In this article, we aim to explain the relationship between perceived risk factors, consumer sentiment, and travelers' behavioral responses. Fig. 1 shows the theoretical framework that pertains to short- and long-term changes in travel behavior and modal preferences in the post-COVID-19 era.

4. Data

The present article uses daily data from March 2, 2020 to January 31, 2022. We employ Apple's Mobility Trend reports to gather information about the use of travel modes other than air travel. These data are published daily and reflect requests for directions in Apple Maps for three transport modes: auto, transit, and walking. Since there is no daily data available for domestic air travelers in the US, this study uses the number of airport checkpoint travelers as a proxy. We collect the number of airport checkpoint travelers, published daily by the Transportation Security Administration (TSA). To estimate the demand for short-, medium-, and long-distance trips, we obtain trip data by distance from the Daily Travel during the COVID-19 Public Health Emergency, reported by the Bureau of Transportation Statistics (Bureau of Transportation Statistics, 2021). The number of trips and travel miles are estimated using a national panel of mobile device data obtained from multiple sources. In this article, we divide daily travel distance into four groups: (1) no trips if residents stay at home, (2) short-distance trips if the distance is less than 50 miles, (3) medium-distance trips if the distance is greater than 50 miles but less than 250 miles, and (4) long-distance trips if the distance is greater than 250 miles.

The new and cumulated cases and deaths due to COVID-19 are used to measure the level of perceived threat of the pandemic. These data are obtained from the Center for Disease Control and Prevention (CDC), which tracks daily COVID-19 illnesses, hospitalizations, and deaths. We use the News Sentiment (NS) and Economic Policy Uncertainty (EPU) indices as proxies for consumer sentiment and economic policy uncertainty, respectively. Using a lexical approach, Shapiro et al. (2020) created a sentiment-scoring model for economics-related news articles. They used news archives and historical news sources, including 24 major US newspapers. Positive values of the index indicate positive consumer sentiment (or confidence). Similarly, the EPU index is a frequently updated measure of uncertainty in economic policy, as outlined by Baker et al. (2016). The EPU index reflects the frequency of policy-related terms in leading US newspapers and other news sources. Finally, this study employs the West Texas Intermediate spot price in Cushing, Oklahoma as a proxy for transportation cost. The oil price data is directly taken from the Energy Information Administration (EIA, 2022). Table 1 reports descriptive statistics for the variables used in this paper.

5. Method

To incorporate the dynamic effects of COVID-19, consumer sentiment, economic uncertainty, and oil prices on travel behavior, we begin with the following function:

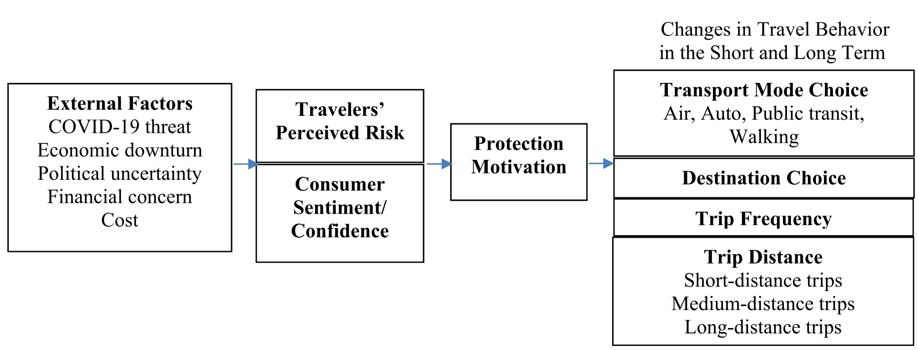

Fig. 1. Protection motivation theory applied to travel behavior and modal preferences in the post COVID-19 era.

Table 1
Summary statistics of the variables.

Variable	Description	Min.	Max.	Mean	St. Dev.
D_t^{air}	Number of airport checkpoint travelers	87,534	2,311,978	1,154,197	628,172
D_t^{auto}	Mobility index (100 = January 13, 2020) for auto	53.53	187.51	125.66	28.10
$D_t^{transit}$	Mobility index (100 = January 13, 2020) for public transit	23.67	138.87	70.75	28.92
$D_t^{walking}$	Mobility index (100 = January 13, 2020) for walking trips	44.06	222.26	128.78	37.59
$D_t^{no\ trip}$	Number of residents staying at home	55,390,150	102,151,030	77,201,782	8,152,369
D_t^{short}	Number of short-distance trips (trip distance <50 miles)	820,100,701	1,489,948,208	1,139,581,155	190,806,327
D_t^{medium}	Number of medium-distance trips (50 miles ≤ trip distance <250 miles)	18,130,080	40,016,712	27,557,077	3,554,901
D_t^{long}	Number of long-distance trips (250 miles ≤ trip distance)	1,342,426	8,343,595	2,773,233	831,434
$COVC_t$	COVID-19 confirmed cases	19	1,383,904	120,327	169,977
$COVD_t$	COVID-19 confirmed deaths	1	4415	1465	984
$ACCOVC_t$	Accumulated COVID-19 confirmed cases	55	75,100,195	24,127,736	18,696,279
$ACCOVD_t$	Accumulated COVID-19 confirmed deaths	6	889,205	421,943	263,393
NS	News Sentiment index	0.32	1.19	0.84	0.24
EPU	Economic Policy Uncertainty index	39.00	807.66	216.51	135.84
$OILP$	Oil prices (crude oil in US dollars per Barrel)	8.91	89.16	54.95	18.48

$$D_t^i = f(COVC_t, COVD_t, ACCOVC_t, ACCOVD_t, NS_t, EPU_t, OILP_t, DUM) \quad (1)$$

where $COVC_t$ is the number of confirmed cases of COVID-19 at time t; $COVD_t$ is the number of confirmed deaths due to COVID-19; $ACCOVC_t$ is the accumulated number of COVID-19 cases; $ACCOVD_t$ is the accumulated number of COVID-19 deaths; NS_t denotes the news sentiment index; EPU_t represents the economic policy uncertainty (EPU) index; and $OILP_t$ represents oil prices. To take into account the US government's response to COVID-19, this paper includes a dummy variable (DUM) that reflects the lockdowns and stay-at-home orders. The variable is set to 1 for the period between March 15 and May 31, 2020 and 0 otherwise. In this study, we employ two dependent variables (D_t^i): 1) the number of trips by transportation mode i (i = air, auto, public transit, and walking) (Model I) and 2) the number of trips by distance group i (i = no trips, short-, medium-, and long-distance trips) (Model II). The number of residents who stayed at home is used for the category of no trips.

By taking the natural log of Equation (1), the function can be expressed as:

$$d_t^i = a_0 + a_1 covc_t + a_2 covd_t + a_3 accovc_t + a_4 accovd_t + a_5 ns_t + a_6 epu_t + a_7 oilp_t + a_8 DUM + u_t, \quad (2)$$

where lower-case letters denote the natural log. The COVID-19 variables can have positive, negative, or insignificant coefficients, depending on the impact of COVID-19 on travel demand for specific modes (Model I) and trip distance groups (Model II). The coefficient of the news sentiment is expected to be positive, as an increase in consumer sentiment can boost demand for travel and tourism services. Similarly, the coefficient of the EPU variable is assumed to be negative as economic policy uncertainty has a negative impact on travel and tourism activities. We expect a negative coefficient of the oil price variable since rising fuel prices can lead to a reduction in travel demand.

In the ARDL model, long-run effects refer to the equilibrium relationship between the variables over a longer period of time. On the other hand, short-run effects in the ARDL model refer to the immediate impact of changes in the variables on each other, and these effects are captured by the lagged values of the variables. Both Equations (1) and (2) only reflect the long-run dynamics of the explanatory variables and do not account for the short-run adjustment mechanism. To allow for short-run feedback from lagged variables, we use the difference in the logarithms of the variable values. Following the ARDL bounds-testing techniques introduced by Pesaran et al. (2001), we specify an error-correction model (ECM) as follows:

$$\begin{aligned}\Delta d_t^i = {} & b_0 + b_1 d_{t-1}^i + b_2 covc_{t-1} + b_3 covd_{t-1} + b_4 accovc_{t-1} + b_5 accovd_{t-1} \\ & + b_6 ns_{t-1} + b_7 epu_{t-1} + b_8 oilp_{t-1} + \lambda DUM + \sum_{k=1}^{p1} \rho_k \Delta d_{t-k}^i + \sum_{k=0}^{p2} \mu_k \Delta covc_{t-k} \\ & + \sum_{k=0}^{p3} \delta_k \Delta covd_{t-k} + \sum_{k=0}^{p4} \eta_k \Delta accovc_{t-k} + \sum_{k=0}^{p5} \pi_k \Delta accovd_{t-k} + \sum_{k=0}^{p6} \gamma_k \Delta ns_{t-k} \\ & + \sum_{k=0}^{p7} \Omega_k \Delta epu_{t-k} + \sum_{k=0}^{p8} o_k \Delta oilp_{t-k} + e_t,\end{aligned} \quad (3)$$

where Δ is the 1st difference operator and $p1$-$p8$ are the lag lengths.

In this specification, the short-run coefficients are represented by the first differences of the variables (Δ), and b_1-b_8 represent the long-run parameters. For the long-run coefficients to be valid, a long-run cointegration relationship must be established among the variables. Therefore, we use the F-statistic to test the joint significance of the lagged levels of variables. Following the approach proposed by Pesaran et al. (2001), we adopt the upper and lower bounds of critical values to test the null hypothesis of no cointegration (H_{CI}: $b_1 = b_2 = \ldots = b_8 = 0$). If the calculated F-statistic is greater than the upper bound of the critical value, we can reject the null hypothesis. If the F-statistic falls below the lower bound of the critical value, then the null hypothesis cannot be rejected. Finally, if the F-statistic lies within the lower and upper bounds, inference is inconclusive.

6. Empirical results

The ARDL bounds-testing approach can be applied even when the variables are of mixed integration order, $I(0)$ and $I(1)$. However, the computed F-statistics are invalid if any of the underlying variables are integrated of order 2, $I(2)$, or higher (Ouattara, 2004). To determine the order of integration, we use the Augmented Dickey-Fuller (ADF) and Phillip Perron (PP) tests. The results of both the ADF and PP tests suggest that all variables are either $I(0)$ or $I(1)$ (Table 2). As none of the series are $I(2)$ or higher, we can proceed with the ARDL bounds test using all the proposed variables for the models.

6.1. Long- and short-run coefficients of model I

Table 3 presents the results of the estimated long-run coefficients and diagnostic statistics for the transport mode equation (Model I). The first step of the ARDL procedure is to test for the presence of a cointegration relationship among the variables. Using the optimal lag order based on the Akaike Information Criterion (AIC), we present the results associated with each optimum model. It is also known that the AIC performs better than other criteria for small samples (Liew, 2004).

Table 2
Results of Augmented Dickey-Fuller (ADF) and Phillip Perron (PP) unit-root tests.

Variable	ADF test		PP test		Conclusion
	Level	First difference	Level	First difference	
d_t^{air}	−2.45*	−18.80**	−1.85	−19.40**	$I(1)$
d_t^{auto}	−6.57**		−5.58**		$I(0)$
$d_t^{transit}$	−2.03	−29.63**	−1.50	−30.80**	$I(1)$
$d_t^{walking}$	−5.01**		−3.74**		$I(0)$
$d_t^{no\ trip}$	−4.58**		−3.95**		$I(0)$
d_t^{short}	−3.44**		−2.24	−41.41**	$I(0)/I(1)$
d_t^{medium}	−10.10**		−10.24**		$I(0)$
d_t^{long}	−11.95**		−5.89**		$I(0)$
$covc_t$	−6.32**		−6.60**		$I(0)$
$covd_t$	−5.72**		−5.10**		$I(0)$
$accovc_t$	−27.11**		−16.31**		$I(0)$
$accovd_t$	−27.60**		−16.97**		$I(0)$
ns_t	−0.73	−20.80**	−0.87	−21.03**	$I(1)$
epu_t	−8.13**		−7.57**		$I(0)$
$oilp_t$	−2.25	−35.42**	−1.42	−36.48**	$I(1)$

Notes: ** and * represent significance at the 5% and 10% level, respectively; Critical values at the 5% and 10% significance levels are −2.87 and −2.57, respectively; The Newey-West Bandwidth is used to calculate the standard error for the PP test.

Table 3
Long-run coefficients of Model I (transport modes).

	Long-run coefficients			
	Air	Auto	Public Transit	Walking
$covc_t$	−0.09**	0.06**	−0.19**	−0.10*
	(-2.32)	(2.37)	(-2.15)	(-1.92)
$covd_t$	−0.17**	0.07**	−0.08	−0.07
	(-2.87)	(2.19)	(-0.73)	(-0.98)
$accovc_t$	−0.70**	0.48**	0.45	0.37
	(-2.86)	(2.28)	(0.74)	(1.22)
$accovd_t$	−0.55**	0.44**	0.19	−0.25
	(-2.22)	(2.26)	(0.28)	(-0.78)
ns_t	0.40**	1.04**	0.43	0.81**
	(2.60)	(2.55)	(1.18)	(2.64)
epu_t	−0.34**	−0.17**	−0.25	−0.26**
	(-3.84)	(-2.96)	(-0.58)	(-2.61)
$oilp_t$	−0.45**	−0.16**	0.06	0.11
	(-3.08)	(-2.71)	(0.23)	(0.67)
DUM	−0.20**	−0.10**	−0.05	−0.11
	(-2.90)	(-2.34)	(-0.24)	(-0.88)
constant	11.40**	4.92**	−2.17	4.37**
	(10.30)	(7.39)	(-1.13)	(3.66)
	Diagnostic statistics			
Adj. R^2	0.97	0.88	0.84	0.94
F	13.18**	9.73**	6.68**	5.09**
LM	3.09*	5.02**	1.20	0.52
	[0.07]	[0.02]	[0.27]	[0.46]
ARCH	0.19	0.25	2.96*	1.92
	[0.66]	[0.61]	[0.08]	[0.16]
RESET	0.89	0.09	2.55	3.03*
	[0.34]	[0.75]	[0.11]	[0.08]

Notes.
a. *T*-values are shown in parentheses.
b. The lower and upper bound critical values at the 5% significance level are 2.32 and 3.50, respectively.
c. *P*-values are reported in square brackets.
d. ** and * represent significance at the 5% and 10% levels, respectively.

Following the approach proposed by Pesaran et al. (2001), two sets of critical values are used to test the null hypothesis of no cointegration. The results show that the calculated *F*-statistics are well above the upper bound critical value at the 5% significance level, indicating the presence of cointegration. To confirm the robustness of the results, various diagnostic tests are performed. The Breusch-Godfrey Lagrange Multiplier (LM) and the Autoregressive Conditional Heteroscedasticity (ARCH) tests are used to check for serial correlation and heteroscedasticity. Additionally, we use the Ramsey's Regression Equation Specification Error Test (RESET) to detect any specification errors. Our results show that the null hypotheses of no autocorrelation, homoscedasticity, and correct specification cannot be rejected at the 5% significance level in most cases.

The results of the long-run analysis indicate that the daily number of COVID-19 cases ($covc_t$) has a significant effect on travel demand for air, auto, and public transit, suggesting that the threat posed by the pandemic is a crucial factor that affects travel behavior in the post-COVID-19 era. An increase in COVID-19 cases has a negative effect on air travel demand (−0.09) and public transit demand (−0.19), but has a positive impact on demand for automobile travel (0.06). These findings imply that during times of high COVID-19 threat, people are more likely to shift from using shared mass transit to personal transportation systems. In addition, the results show that the daily number of COVID-19 deaths ($covd_t$) has a significant influence on demand for air and auto travel, indicating that a rise in deaths leads to a reduction in air traffic volume (−0.17) and an increase in automobile use (0.07). We also find that public transit and walking trips are insignificantly associated with daily COVID-19 deaths. In this study, accumulated cases and deaths were used as control variables to determine the net effect of the daily conditions of COVID-19 on travel demand, and it was found that these variables have mixed effects on travel demand. For example, the accumulated cases ($accovc_t$) and deaths ($accovd_t$) of COVID-19 are strongly associated with demand for air and auto travel, while they have an insignificant effect on demand for public transit and walking.

Consumer sentiment (ns_t) has a positive long-term impact on travel demand, and its effect is statistically significant at the 5% significance level for air, auto, and walking trips. A rise in consumer sentiment is found to increase travel demand for air (0.40) and auto (1.04), implying that consumer's positive expectations regarding future economic and financial prospects increase expenditure and consumption of these transport services. Similarly, an uncertainty shock (epu_t) is significantly associated with travel demand. Higher uncertainty, as measured by the EPU index, is negatively associated with air (−0.34) and auto (−0.17) travel, indicating that consumers reduce their frequency and cost of these transportation services if they have pessimistic expectations for the future state of the economy and policy. These results are in line with the findings of Gholipour et al. (2022) that consumer sentiment and economic policy uncertainty are crucial non-economic drivers of tourism demand. Their study found that an increase in consumer confidence boosts travel demand, while uncertainty shocks decrease travel demand. Furthermore, the coefficient of the oil price variable ($oilp_t$) has a negative sign, as expected, and its impact is statistically significant for air and auto travel, indicating that rising fuel prices reduce demand for these transportation modes. On the other hand, the impact of oil prices on demand for public transit and walking is not statistically significant. Lockdowns and stay-at-home orders (*DUM*) have a significant long-term effect on air and automobile travel demand, while they are insignificantly associated with demand for public transit and walking. The results suggest that these government policies have altered travel patterns, particularly for air and car travel, in the US.

Table 4 provides the short-run elasticities of travel demand. As the lag order increases, the *F*-statistic becomes highly sensitive to the lag length. Therefore, we use the error-correction term (EC_{t-1}) as an alternative way to confirm the presence of cointegration. When the coefficient of EC_{t-1} is negative and statistically significant, it indicates convergence towards cointegration. For all transport modes, the error-correction term carries a significant coefficient at least at the 5% significance level, and the expected negative sign confirms the presence of cointegration.

The short-run results indicate that daily and accumulated COVID-19 deaths have a significant impact on travel behavior in the current period

Table 4
Short-run coefficients of Model I (transport modes).

Mode	Variable	Lag 0	1	2	3	EC_{t-1}
Air	$\Delta covc_t$	0.03	−0.06*	−0.15**	−0.01	−0.32**
		(0.90)	(-1.72)	(-4.50)	(-0.56)	(-10.36)
	$\Delta covd_t$	−0.07**	−0.07**	0.13**		
		(-3.28)	(-3.12)	(6.06)		
	$\Delta accovc_t$	−0.03	0.19	0.46*		
		(-0.00)	(0.48)	(1.65)		
	$\Delta accovd_t$	−0.69**	−0.89**	−0.73**		
		(-2.58)	(-2.95)	(-2.20)		
	Δns_t	0.93	0.39	0.11	0.06	
		(0.81)	(1.14)	(0.33)	(0.20)	
	Δepu_t	−0.03	−0.02	−0.01	0.01	
		(-1.12)	(-1.18)	(-0.60)	(0.21)	
	$\Delta oilp_t$	−0.14**				
		(-2.94)				
	DUM	−0.06**				
		(-2.86)				
Auto	$\Delta covc_t$	−0.01	−0.05**			−0.34**
		(-0.45)	(-2.41)			(-7.67)
	$\Delta covd_t$	0.14**	0.04**	0.05**	0.11**	
		(8.58)	(2.73)	(4.19)	(8.86)	
	$\Delta accovc_t$	0.01				
		(0.28)				
	$\Delta accovd_t$	0.50**	0.16	−0.12	−0.37**	
		(3.44)	(1.11)	(-0.88)	(-2.74)	
	Δns_t	0.79	0.28	0.42*	−0.65	
		(1.28)	(1.06)	(1.66)	(-1.52)	
	Δepu_t	−0.04**	0.01	−0.02**	−0.00	
		(-3.42)	(1.46)	(-2.20)	(-0.27)	
	$\Delta oilp_t$	−0.05**				
		(-2.66)				
	DUM	−0.03**				
		(-2.37)				
Public Transit	$\Delta covc_t$	0.00	−0.02	0.01	−0.09**	−0.07**
		(0.22)	(-1.38)	(0.71)	(-6.15)	(-5.56)
	$\Delta covd_t$	−0.06**	0.00	0.02*	0.07**	
		(-5.02)	(0.32)	(1.77)	(6.74)	
	$\Delta accovc_t$	−0.15*	0.01	−0.04	−0.23**	
		(-1.84)	(0.08)	(-0.46)	(-2.44)	
	$\Delta accovd_t$	−0.02**				
		(-5.28)				
	Δns_t	0.32	−0.08	0.06	0.24	
		(0.84)	(-0.53)	(0.38)	(1.51)	
	Δepu_t	−0.01				
		(-0.68)				
	$\Delta oilp_t$	0.01				
		(0.23)				
	DUM	−0.01**				
		(-2.24)				
Walking	$\Delta covc_t$	0.05**	−0.01	0.02	−0.14**	−0.18**
		(2.35)	(-0.11)	(0.60)	(-6.43)	(-5.55)
	$\Delta covd_t$	0.09**	−0.01	0.04**	0.21**	
		(5.22)	(-0.53)	(2.75)	(14.74)	
	$\Delta accovc_t$	−0.56*				
		(-1.92)				
	$\Delta accovd_t$	0.13**	−0.07	0.01	−0.25**	
		(2.45)	(-0.53)	(0.08)	(-2.89)	
	Δns_t	0.81	−0.22	0.29	−0.54**	
		(0.83)	(-0.92)	(1.23)	(-2.33)	
	Δepu_t	0.03	0.00	−0.02*	−0.01	
		(0.70)	(0.13)	(-1.65)	(-1.36)	
	$\Delta oilp_t$	0.02				
		(0.66)				
	DUM	−0.02				
		(-0.87)				

Notes.
a. *T*-values are shown in parentheses.
b. ** and * represent significance at the 5% and 10% levels, respectively.

(when lag = 0). The results reveal that in the current period, an increase in COVID-19 deaths, represented by $\Delta covd_t$ and $\Delta accovd_t$, has a significant effect on travel demand in all cases. Escalating deaths due to COVID-19 reduce travel demand for air and public transit while promoting the use of private autos and non-motorized travel (walking). As De Vos (2020) pointed out, social distancing due to COVID-19 has resulted in social isolation and limited physical activity. Walking can encourage people to achieve high levels of physical activity and subjective well-being, which may lead to increased demand for walking trips.

Consumer sentiment (Δns_t) appears to have an insignificant influence on demand for all transport modes at the 5% significance level. This suggests that sentiment shocks do not significantly affect travel behavior in the short term. Economic policy uncertainty (Δepu_t) is also found to be insignificantly associated with travel demand in all cases, except automobile use (−0.04). Our results based on these sentiment and uncertainty proxies indicate that US travelers are insensitive to sentiment and uncertainty shocks in the short run. In contrast, we observe a significant short-run impact of oil prices on demand for air and auto travel. Using the zero-lag length, oil price changes ($\Delta oilp_t$) are negatively associated with demand for air and auto travel, while they have an insignificant influence on transit and walking trips. Lockdowns and stay-at-home orders (*DUM*) have a negative coefficient in all cases, and their effects are statistically significant at the 5% significance level for air, auto, and public transit.

6.2. Long- and short-run coefficients of model II

Turning our attention to the trip distance equation (Model II), Table 5 reports the long-run results for four groups: staying-at-home and

Table 5
Long-run coefficients of Model II (trips by distance).

	Long-run coefficients			
	No trips	Short-distance trips	Medium-distance trips	Long-distance trips
$covc_t$	0.07**	−0.04	−0.04	−0.08**
	(2.64)	(-1.47)	(-1.19)	(-2.64)
$covd_t$	−0.12**	−0.12	−0.04	−0.07**
	(-2.85)	(-1.27)	(-0.87)	(-2.53)
$accovc_t$	0.79**	−0.66	−0.28**	−0.91**
	(3.59)	(-1.15)	(-2.80)	(-2.83)
$accovd_t$	−1.10**	−0.46**	−0.29**	−0.68**
	(-3.05)	(-2.36)	(-1.96)	(-2.30)
ns_t	−0.42**	0.66**	0.28**	1.34**
	(-2.20)	(2.81)	(3.05)	(2.61)
epu_t	−0.05	−0.15	−0.13	−0.11**
	(-1.08)	(-1.41)	(-0.71)	(-2.72)
$oilp_t$	0.27	−0.50**	0.06	−0.34**
	(0.85)	(-3.21)	(0.63)	(-3.47)
DUM	0.08	−0.25**	−0.18**	−0.35**
	(1.08)	(-2.73)	(-2.40)	(-2.52)
constant	20.52**	21.75**	18.76**	12.41**
	(24.60)	(24.25)	(23.49)	(6.45)
	Diagnostic statistics			
Adj. R^2	0.91	0.94	0.71	0.80
F	7.24**	4.21**	7.68**	3.91**
LM	1.34	7.86**	0.12	0.69
	[0.24]	[0.01]	[0.72]	[0.40]
ARCH	0.42	1.51	3.21*	3.73*
	[0.51]	[0.21]	[0.07]	[0.05]
RESET	1.84	0.31	2.14	1.21
	[0.17]	[0.57]	[0.14]	[0.22]

Notes.
a. *T*-values are shown in parentheses.
b. The lower and upper bound critical values at the 5% significance level are 2.32 and 3.50, respectively.
c. *P*-values are reported in square brackets.
d. ** and * represent significance at the 5% and 10% levels, respectively.

short-, medium-, and long-distance trips. For all groups, the calculated F-statistic is above the upper limit critical value at the 5% significance level, indicating that all the variables are cointegrated. In addition, the results of the diagnostic tests indicate that the null hypotheses of no autocorrelation, homoscedasticity, and correct specification cannot be rejected at the 5% significance level in most cases, suggesting that Model II is generally well specified without serial correlation and heteroscedasticity.

The long-run results show that for the no trip and long-distance trip groups, the daily cases and deaths of COVID-19 are significantly associated with travel demand. An increase in new COVID-19 cases has a positive effect on the number of residents staying at home (0.07), while it has a negative influence on demand for long-distance trips (−0.08). Consistent with the findings of Abdullah et al. (2020), our results indicate that as the COVID-19 pandemic worsens, risk-averse travelers reduce the frequency of their trips and avoid making long-distance trips. The coefficients for the accumulated COVID-19 case and death variables exhibit similar travel behavior patterns. An increase in the accumulated number of COVID-19 cases has a positive impact on the number of residents who stay at home (0.79), while it has a negative effect on demand for medium-distance trips (−0.28) and long-distance trips (−0.91).

Our results also demonstrate that accumulated number of COVID-19 deaths has a significant negative effect on demand for short-, medium-, and long-distance travel. One reason for these findings is that COVID-19 has altered consumers' shopping and purchasing behaviors. Using 27 European country data, Campisi et al. (2021) found a strong correlation between COVID-19 and the GDP component related to internet and e-commerce use. Additionally, Villa and Monzón (2021) noted that consumers adopted new shopping and consumption habits during the lockdown to avoid in-person contact at stores. As a result, the increase in e-commerce may have a negative impact on travel demand, especially for short- and medium-distance trips.

In conjunction with the findings of Model I, we conclude that demand for long-distance trips, such as those by air and car, is sensitive to changes in COVID-19 cases and deaths in the long term. These results are consistent with previous evidence presented by Truong and Truong (2021), which shows distinct correlations between new COVID-19 cases and deaths and the number of trips by distance. Their empirical results indicated that both COVID-19 deaths and cases are negatively correlated with trips between 250 and 500 miles and trips longer than 250 miles.

The short-run coefficients of Model II are provided in Table 6. For all groups, the error-correction term has a negative coefficient and is statistically significant at the 5% significance level, confirming cointegration. Concerning the influence of COVID-19 deaths on travel demand, we find mixed results for the selected groups. For example, daily COVID-19 deaths have a positive impact on the number of people staying at home (0.02) and short-distance trips (0.02), but a negative effect on demand for medium-distance trips (−0.06) and long-distance trips (−0.05). The short-run results indicate that in the current period, consumer sentiment and economic policy uncertainty tend to be insignificantly associated with the daily number of trips. For instance, consumer sentiment does not have a significant impact on travel demand in all cases. Furthermore, uncertainty shocks have a significant negative effect on demand for medium-distance trips only. Our analysis reveals that changes in oil prices ($\Delta oilp_t$) play a crucial role in short-term travel behavior. A rise in oil prices significantly decreases the number of short and long-distance trips, while it has no significant effect on medium-distance trips. These findings suggest that the relationship between oil prices and travel behavior varies depending on the distance of the trip. Our results also confirm that lockdowns and stay-at-home orders have a significant detrimental impact on the short-, medium-, and long-distance trips, implying that mandatory stay-at-home orders effectively reduced population movement and the transmission of COVID-19 in the US.

Table 6
Short-run coefficients of Model II (trips by distance).

	Variable	Lag				EC_{t-1}
		0	1	2	3	
No trips	$\Delta covc_t$	−0.01* (-1.66)	0.01 (0.44)	−0.01** (-2.08)		−0.14** (-7.98)
	$\Delta covd_t$	0.02** (3.36)	−0.01 (-0.33)	−0.00 (-0.72)	−0.02** (-4.44)	
	$\Delta accovc_t$	−0.05 (-0.50)	0.03 (0.58)	0.01 (0.23)	−0.12** (-2.76)	
	$\Delta accovd_t$	0.15 (1.27)				
	Δns_t	0.08 (1.25)	−0.11 (-1.28)	0.04 (0.49)	0.09 (1.02)	
	Δepu_t	−0.01 (-0.25)	0.01 (1.51)	0.01** (1.96)		
	$\Delta oilp_t$	0.03** (2.43)				
	DUM	0.01 (1.18)				
Short-distance trips	$\Delta covc_t$	0.02** (2.18)	0.01 (1.18)	0.01 (1.34)		−0.09** (-5.71)
	$\Delta covd_t$	0.02** (2.18)	−0.01 (-1.21)	−0.01 (-0.51)	0.02** (3.03)	
	$\Delta accovc_t$	−0.37** (-4.00)	−0.04 (-0.73)	−0.07 (-1.22)	−0.11* (-1.87)	
	$\Delta accovd_t$	0.09** (2.20)				
	Δns_t	−0.07 (-0.86)	0.10 (0.83)	−0.20** (-2.18)		
	Δepu_t	−0.00 (-0.23)				
	$\Delta oilp_t$	−0.02** (-3.00)				
	DUM	−0.03** (-2.32)				
Medium-distance trips	$\Delta covc_t$	0.09** (4.33)	−0.02 (-1.06)	0.07** (3.45)	−0.04** (-2.22)	−0.25** (-6.77)
	$\Delta covd_t$	−0.06** (-4.30)	−0.01 (-0.07)	0.00 (0.73)	−0.09** (-7.95)	
	$\Delta accovc_t$	−0.07* (-1.89)				
	$\Delta accovd_t$	−0.31** (-2.77)				
	Δns_t	0.31* (1.77)	0.42* (1.85)			
	Δepu_t	−0.03** (-2.19)	−0.01 (-0.00)	−0.02* (-1.92)	−0.01 (-1.10)	
	$\Delta oilp_t$	0.02 (0.63)				
	DUM	−0.04** (-2.33)				
Long-distance trips	$\Delta covc_t$	0.01 (1.64)	−0.04 (-1.41)	0.12 (1.03)	−0.08** (-2.61)	−0.41** (-8.75)
	$\Delta covd_t$	−0.05** (-2.31)	0.00 (0.18)	0.01 (0.65)	0.18** (3.47)	
	$\Delta accovc_t$	−0.01 (-0.11)				
	$\Delta accovd_t$	−0.45** (-2.60)	0.07 (0.41)			
	Δns_t	0.34 (1.50)	0.48** (2.15)	−0.01 (-0.02)		
	Δepu_t	−0.02* (-1.89)	−0.01 (-0.08)	−0.02* (-1.76)	−0.02* (-1.75)	
	$\Delta oilp_t$	−0.05** (-3.30)				
	DUM	−0.08** (-2.83)				

Notes.
a. *T*-values are shown in parentheses.
b. ** and * represent significance at the 5% and 10% levels, respectively.

7. Conclusion

Given the emerging evidence that COVID-19 has heightened levels of health risk and economic uncertainty, this paper aims to investigate the effects of COVID-19 threat, consumer sentiment, economic policy uncertainty, and oil prices on travel patterns. Using the US daily data, we provide new empirical evidence that consumer sentiment and economic policy uncertainty are important determinants of travel behavior changes during the COVID-19 crisis. With consumer behavior having been substantially altered by the COVID-19 crisis and economic uncertainty, this paper provides important findings and policy implications, as follows.

First, our study reveals that consumer sentiment is a crucial factor affecting travel behavior in the long term. We find a significant positive effect of consumer sentiment on demand for air and auto travel, suggesting that a surge in consumer confidence can boost demand for these modes of transportation in the long run. By utilizing the Economic Policy Uncertainty (EPU) index, we confirm that economic and political shocks have a negative effect on air and auto travel demand. Based on these findings, demand for air and auto travel is likely to rise in the long term if consumer confidence improves in the US. Sustainable and resilient economic recovery is a vital aspect of the US crisis management and post-recovery plans. According to the Organisation for Economic Cooperation and Development (OECD, 2020), COVID-19 recovery policies should aim to stimulate investment and promote behavioral adjustments that will reduce the probability of future economic uncertainty shocks. Rather than focusing solely on short-term economic relief, these policies should be designed to improve long-term economic resilience. Our research aligns with these policies and strategies, which aim to increase consumer confidence in future economic prosperity and well-being.

Second, our long-run results suggest that an improvement in consumer sentiment boosts travel demand across all trip distance categories, while it has a negative impact on the number of residents staying at home. The correlation between consumer confidence and travel demand is particularly strong for long-distance trips by air and car. Therefore, policies that enhance consumer confidence, such as implementing monetary policies aimed at lowering interest rates or economic stimulus programs, may have a positive impact on demand for long-distance travel. However, the short-run analysis demonstrates that economic sentiment and uncertainty shocks tend to be insignificantly associated with travel demand across all modes of transportation. A possible explanation for these findings is that US consumers may adopt a wait-and-see approach towards fluctuating economic uncertainty. For instance, consumers who drive or fly may not immediately alter their transportation mode in response to short-term economic uncertainty shocks, but they will eventually adjust in the long term. Given the significant long-term impact of economic uncertainty on travel behavior, it is important for transport authorities and planners to consider the long-term effect of uncertainty shocks when predicting post-pandemic travel behaviors and demand. Additionally, it may be necessary to re-evaluate infrastructure investments in light of the potential long-term impact of uncertainty shocks on travel behavior and demand.

Third, we find that the perceived threat of COVID-19 is an important long-term factor affecting travel behavior. Our results show that an increase in COVID-19 cases reduces demand for air and public transit travel, while stimulating demand for auto travel. This evidence suggests that a high level of perceived pandemic threat leads to a decrease in the usage of shared-use mass transport systems and an increase in the use of private transportation options. These findings support Abdullah et al.'s (2021) conclusion that there has been a modal shift from public transport to personal vehicles for long-distance travel. With COVID-19 altering mode preferences and travel behavior patterns, transportation managers may need to develop operation plans and strategies that account for different pandemic levels. For example, during a low pandemic level, transportation managers may focus on maintaining the current transportation services, such as accommodating the growing demand for air travel. However, in the case of a high pandemic level, transportation managers may need to adjust their services to meet the changing travel patterns of passengers, such as reducing service frequency, limiting capacity on public transportation vehicles, and closing certain routes.

Finally, our study shows a significant effect of oil prices on demand for air and auto travel. Oil prices are significantly correlated with demand for long-distance trips in the short and long term, indicating that transportation costs play a crucial role in shaping travel patterns in the post-COVID-19 era. This further implies that transportation authorities and planners should monitor the oil price trends when making operational plans and strategies. For example, the recent Ukraine-Russian conflict has driven US oil prices to a record high level, surpassing $100 per barrel (Iacurci, 2022), making volatile energy prices a potential challenge for the air travel sector. This highlights the need for the US airline industry to develop a more comprehensive strategy to cope with fluctuating oil prices and reevaluate its hedging policies.

The present article has some limitations that should be taken into consideration for future research. For example, due to the limited time-series data available (2020–2022), we were unable to capture the true long-run effect that could last more than a decade. Future studies should utilize longer time-series data, such as monthly or quarterly data, to further investigate the long-term effects of economic uncertainty shocks on travel behavior. This line of research will enhance our understanding of the dynamic effects of the selected variables on travel behavior patterns. Another limitation of this article is that it did not take into account other variables beyond economics. Future research could explore the effects of socio-psychological and product-related factors such as personal characteristics, motivation, attitude, social values, and involvement on travel behavior patterns. This could provide a more comprehensive understanding of what drives travel and tourism demand in the post-COVID-19 era.

Author contributions

Junwook Chi is the sole author of this paper and contributes to all aspects, including Data Curation, Formal Analysis, Investigation, and Writing - Original Draft & Reviewing and Editing.

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Data availability

Data will be made available on request.

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