ESSAYS ON RECREATIONAL TRAVEL AND COVID-19: AN ECONOMIC ANALYSIS OF CANCELED TRIPS

by

KEHINDE ELIZABETH OJO

(Under the Direction of SUSANA FERREIRA and JOHN SALAZAR)

ABSTRACT

This dissertation comprises three essays that develop two different conceptual frameworks on individual behavior to provide information on how the COVID-19 pandemic affects recreational travel. The second chapter develops a model that extends expected utility theory by incorporating subjective norms and perceived behavioral control from the theory of planned behavior. Subjective norms are the perception of other people's approval of an individual's particular behavior. Chapter two examines the factors that influenced individuals to cancel or postpone intended or planned leisure trips in 2020 in the United States. The results support the study hypothesis that, in addition to the perceived risk of contracting or transmitting COVID-19 while traveling, the decision to engage in recreational travel depends on subjective norms. The third chapter develops a conceptual model to show the effects of subjective norms on recreation or leisure demand and values. It tests the model empirically and shows that the subjective norms variable is a recreation demand shifter. The model estimates a net decrease of approximately 1,800 in consumer surplus (CS) or willingness to pay (WTP) for visitors to Georgia associated with COVID-19. The fourth chapter conducts economic impact analysis of COVID-19 on the economy of the state of Georgia, focusing on canceled/postponed leisure trips. The economic impact analysis shows that canceled trips to Georgia generated a reduction of approximately $9.03 million in total output for day trips and $30.51 million for overnight trips. These results could provide tourism and travel stakeholders and policymakers in Georgia with insights into the differences between the economic impact generated for day and overnight trips, thus enabling them to design policies that could enhance recovery strategies for the Georgia tourism industry.

INDEX WORDS: COVID-19 PANDEMIC, RECREATIONAL TRAVEL, EXPECTED UTILITY THEORY, THEORY OF PLANNED BEHAVIOR, SUBJECTIVE NORMS, TRAVEL COST, RECREATION DEMAND MODEL, ECONOMIC IMPACT

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DEDICATION

I dedicate this dissertation to God almighty for His strength, help, courage, and wisdom throughout my program and in writing this dissertation.

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CHAPTER 1

BACKGROUND AND INTRODUCTION

The importance of the travel and tourism sector in the United States, which contributes 2.8% of the annual GDP, cannot be overlooked. This sector provided 7.8 million jobs and $1.62 trillion in output in 2017 (NTTO, 2018). Travel disruptions such as natural disasters, terrorism, and health and safety crises profoundly impact tourism (Ghaderi et al., 2013, Samitas et al., 2018). This travel disruption includes the COVID-19 pandemic. To contain the spread of COVID-19, lockdown (stay-at-home orders) and travel restrictions were implemented worldwide and in approximately 42 states in the United States from mid-March 2020 (CDC, 2020). These measures exerted enormous economic impacts, especially in the travel and tourism industry. Subsequently, the U.S. travel economy experienced $492 billion in cumulative losses from March 2020 to January 2021, resulting in a $64 billion loss in tax revenue at the federal, state, and local levels (U.S. Travel Association, 2021).

COVID-19, a severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), was discovered in Wuhan, Hubei, China, in December 2019. As of January 2, 2020, up to 41 patients had been identified as having tested positive for the coronavirus and were admitted to hospitals in China (Huang et al., 2020). Due to the widespread virus, Wuhan faced lockdown, a measure to slow the spread of the virus. By the middle of March 2020, the coronavirus spread had stabilized in China at approximately 80,000 confirmed cases. However, as stability was reached in China, the virus had also spread to approximately 223 countries and all continents. As 2020 progressed, the number of confirmed COVID-19 cases doubled, the death toll increased (Worldometer, 2022), and the infection rate skyrocketed worldwide through community transmission. As of the time of writing this dissertation, on June 18, 2022, approximately 223 countries have confirmed positive coronavirus cases, with 544,040,043 confirmed cases and 6,340,199 deaths (Worldometer, 2022). The country with the highest number of confirmed cases is the United States, with a total of 87,981,568 cases and 1,038,289 deaths from January 21, 2020 (when the first COVID-19 cases were confirmed in the United States) to June 18, 2022 (Worldometer, 2022).

It is crucial that policymakers and travel and tourism stakeholders understand how COVID-19 has impacted the leisure and recreation industry in all U.S. regions. Numerous studies have examined the impact of COVID-19 on tourism worldwide and across the United States, including its impact on consumer behavior, outdoor recreation, the hotel and lodging industry, and the food sector (Bae & Chang, 2020; Gössling et al., 2020; Han et al., 2022; Higgins-Desbiolles, 2020; Hoque et al., 2020; Landry et al., 2021; Qui et al., 2020; Yeh, 2020). For instance, Landry et al. (2021) estimated the impacts of the COVID-19 pandemic on visits to public outdoor recreation sites and found that the pandemic negatively affected recreational visits and values. Specifically, their results showed a 19% loss in consumer surplus per outdoor recreation participant associated with COVID-19. Gössling et al. (2020) examined whether COVID-19 was an “unknowable risk” and assessed the reported impacts of COVID-19 on global tourism. Yeh (2020) used a qualitative research approach to examine the tourism crisis and disaster management during COVID-19 in 2020. Yeh (2020) found that open communication is key to effectively tackling the pandemic and Government-sponsored loans are also essential to the continued existence of the tourism industry.

Other research examining the impact of COVID-19 includes a study by Bae and Chang (2020), who used the health belief model (HBM) and an extended theory of planned behavior (eTPB) to examine the impact of risk perception regarding COVID-19 on behavioral intention toward “untact” (no contact) tourism. Huang et al. (2020) analyzed the effect of the COVID-19 pandemic on the United States hospitality industry. They found that a 20–30% reduction of nonsalaried workers in the food/drink and leisure/entertainment sectors from March to April 2020 was related with business closure policies associated with COVID-19. Despite the immense literature on COVID-19 impacts on the tourism industry, there remains a need to obtain as much information as possible on the effects of COVID-19 on several sectors. Therefore, my research used data that gathered information on the impact of COVID-19 on travel, sentiment, and behavior to estimate the impact of COVID-19 on the travel and tourism industry. Beyond examining the implications of the COVID-19 pandemic, my research also developed a behavioral models that accurately explains people’s behavior, thereby filling gaps in decision-theoretic literature and recreation demand literature. Chapters 2 to 4 of this dissertation explain explicitly how my research fills these gaps.

Chapter 2 is placed in the context of behavioral and tourism literature. Many previous studies on tourism, leisure, and hospitality management have relied on the theory of planned behavior (TPB), particularly to analyze consumer behavior (e.g., Huang et al., 2020; Joo et al., 2020; Lee et al., 2019; Meng et al., 2020; Petrescu & Bran, 2020; Ulker-Demirel & Ciftci, 2020). However, within this literature, it has been noted that the TPB fails to fully reflect behavioral change (Matsumori et al., 2019), as it disregards some underlying factors addressed through behavioral economic models that are centered mainly on uncertainty. The expected utility theory (EUT) is one model commonly used in economics to make decisions under uncertainty. Similarly, EUT does not capture the sociopsychological factors involved in decision-making, which are better accounted for within the TPB. Therefore, to explain behavioral change more accurately, we combined EUT and the TPB to develop a new model – extended expected utility theory (extended EUT) – to explain human behavior in leisure travel.

We used EUT and the new extended EUT to examine the factors that influenced individuals to cancel/postpone intended or planned leisure trips in 2020 in the United States during COVID-19. Our results showed that the extended EUT is preferable compared to EUT using model selection criteria, such as the Akaike information criterion and Bayesian information criterion. The results also showed that risk perception and subjective norms are the most important factors that influences individual decisions. An in-depth look into the nature of risk perception showed that health risk is more essential than the financial risk when an individual in the United States cancels/postpones leisure travel.

Chapters 3 and 4 focus on the impact of the COVID-19 pandemic on the state of Georgia economy. Tourism is essential to Georgia's economy, generating 478,000 jobs and 3.4 billion in state and local tax revenue in 2018. Unfortunately, the tourism industry has been one of the sectors hardest hit by the COVID-19 pandemic (U.S. Travel Association, 2021). COVID-19 reduced travel spending by $11.8 billion in 2020, and 70% of hotel employees were laid off or furloughed at the onset of the pandemic (AHLA, 2020). Given the significant contributions of tourism to the state of Georgia economy and the negative impact of COVID-19 on this sector, we sought to quantify the impacts of the COVID-19 pandemic on both tourists and the state economy.

Subjective norms are essential to include in a recreation model because they account for sociopsychological factors in tourist decision-making. Specifically, in Chapter 3 of this dissertation, the effect of subjective norms was examined in the valuation of environmental commodities. Specifically, we developed a conceptual model to explain the effects of subjective norms on non-market commodity valuation. We empirically tested the effects of subjective norms on recreation demand and values. In particular, we analyzed the effects of subjective norms using the travel cost recreation model first to test the effects of subjective norms and other explanatory variables on tourists' decisions to cancel or postpone recreation/leisure trips to the state of Georgia. Secondly, we estimated the net economic value or willingness-to-pay (WTP) of tourists who canceled or postponed recreation/leisure trips.

In Chapter 4, we used IMPLAN (impact analysis for planning), an input-output model, to estimate the economic growth and interdependence of canceled and postponed leisure trips due to COVID-19 on the State of Georgia economy. The remainder of this dissertation proceeds as follows: The next sections provide detailed information in chapter 2, followed by chapters 3 and 4. The last chapter describes the implications and conclusions of this dissertation.

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CHAPTER 2

RECREATIONAL TRAVEL BEHAVIOR AND COVID-19: INSIGHTS FROM EXPECTED UTILITY AND THE THEORY OF PLANNED BEHAVIOR[1]

[1] Ojo, K. E., Ferreira, S., Salazar, J., Bergstrom, J., & Woosnam, K. M. (2022). Recreational travel behavior and COVID-19: Insights from expected utility and the theory of planned behavior. *Tourism Economics*, 13548166211059642. https://doi.org/10.1177%2F13548166211059642. Reprinted here with permission of the publisher.

2.1. Abstract

Understanding what factors play a role in people's decisions to travel during a pandemic is important to public health officials and to stakeholders in the travel and tourism industry in the United States (US) and worldwide. This study examines factors influencing people's decisions to cancel/postpone recreational travel within the US amidst the COVID-19 pandemic. Our conceptual framework extends the Expected Utility model, commonly used in economics to model decisions under risk and uncertainty, to incorporate subjective norms and perceived behavioral control from the Theory of Planned Behavior. Our results suggest that risk perceptions, subjective norms, and concerns over transmitting COVID-19 to others play a significant role in the decision to cancel and postpone recreational travel. Results also suggest that perceived behavioral control may be less relevant to travel decisions when traveling involves elevated health risks.

Keywords: COVID-19 Pandemic, Expected Utility Theory, Theory of Planned Behavior, Risk Perception, Subjective Norms, Perceived Behavioral Control

2.2. Introduction

In addition to general risks a person traveling for leisure faces including being injured in an accident or developing stomach problems, travelling during a pandemic poses qualitatively different risks of contracting and spreading a potentially lethal disease. This paper examines factors that influence people's decisions to cancel or postpone recreational travel within the United States (US) amidst the COVID-19 pandemic. Understanding what factors play a role in people's decisions to travel during a pandemic is important because of the consequences on both personal and public health and on the travel and tourism industry. Travel is a strong force in the emergence and spread of disease. One of the first actions of public health officials worldwide at the outset of the COVID-19 pandemic was to issue stay-at-home orders restricting travel and gatherings to reduce activities associated with community spread of COVID-19, including population movement and close person-to-person contact outside the household (Moreland et al., 2020). During the COVID-19 pandemic, travel restrictions and decision by millions of individuals to cancel or postpone travel imposed huge costs to stakeholders in the travel and tourism industry in the US and worldwide. According to the US Travel Association, since the beginning of March 2020 through the end of the year, the pandemic resulted in $492 billion in cumulative losses for the US travel economy (US Travel Association 2021).

In this paper, we model traveler behavior using a conceptual framework based on Expected Utility Theory (EUT) where individuals weigh the utility derived from traveling with the disutility of being infected by COVID-19 (or infecting others), using subjective risk perceptions. The EUT model is expanded to incorporate subjective norms and perceived behavioral control from the theory of planned behavior (TPB) (Huang et al., 2020). Subjective norms are the perception of other people's approval of an individual’s particular behavior (Ajen, 1991), while perceived behavioral control refers to an individual's perception of the capacity to perform the behavior (Bish et al., 2000). We hypothesize that, in addition to the perceived risk of contracting or transmitting COVID-19 while traveling, the decision to engage in recreational travel depends on subjective norms as well as perceived behavioral control, particularly given public appeals from government to engage in social-distancing and travel restrictions. Our analysis tests the relative strength of these predictors.

Many previous studies on tourism, leisure, and hospitality management rely on the TPB, particularly to analyze consumer behavior (e.g., Joo et al., 2020, Petrescu & Bran, 2020, Ulker-Demirel & Giftci, 2020, Meng et al., 2020, Huang et al., 2020, Lee et al., 2019). However, within this literature, it has been noted that the TPB fails to fully reflect behavioral change (Matsumori et al., 2019), disregarding some underlying factors addressed through behavioral economic models, especially centered on uncertainty. The Expected Utility Theory (EUT) is one such model commonly used in economics for making decisions under uncertainty. Similarly, EUT does not capture the social psychological factors involved in decision making, which are better accounted for within the TPB. Therefore, to more accurately explain behavioral change, the current work uses the EUT and the TPB in a complementary fashion. To our knowledge, only two works have combined the EUT and TPB frameworks to explain behavioral change. Matsumori et al. (2019) used an expected utility model to extend the theory of planned behavior so as to derive a decision-theoretic model of behavioral change. Similarly, Borges et al., (2015) used the TPB to extend EUT to explain farmers' innovation adoption decisions. Not only were these works outside the realm of travel and tourism, they were theoretical in nature, stopping short of empirically evaluating their proposed models. Our study is the first to combine EUT with TPB in an effort to explain behavioral change concerning leisure travel from theoretical and empirical perspectives.

To estimate an empirical model of travel sentiment and behavior based on the conceptual framework, we used survey data collected in two waves, the first one in June-July 2020 and the second one in October 2020. The survey was administered through Qualtrics, Inc. who randomly selected a representative sample of 1,454 US residents (541 for wave 1, and 913 for wave 2) from its proprietary panel covering 48 states in the US. The survey gathered information on travel behavioral change, subjective norms, perceived behavioral control, risk perception, health risks, financial risks, and a wide range of socio-demographic variables. One advantage of analyzing the same survey conducted at two different points in time is that it allows us to test if the strength of the predictors of travel decisions changes over time, perhaps as people were getting more informed, developing coping strategies, or experiencing COVID-19 fatigue.

Our results suggest that risk perceptions and subjective norms have played a significant role in the decision of US residents to cancel or postpone recreation travel due to the COVID-19 threat. The effect of risk perceptions on the decision to cancel recreational travel is statistically significant and has decreased over time (i.e., from wave 1 to wave 2). The decline was not found to be statistically significant, however, perhaps because of the short period between waves. Unsurprisingly, health risks play a greater role in the decision to cancel recreational trips than financial risks. Concern about infecting others matters greatly: all individuals who canceled leisure trips in our survey indicated that they were concerned about transmitting COVID-19 at their travel destination or upon their return. On the other hand, perceived behavioral control was not a significant factor for canceling/postponing recreational travel in our study.

Our contribution to the literature is threefold. Firstly, we evaluate consumer behavior in an industry that is especially susceptible to risk, namely tourism, by combining two theoretical frameworks, EUT and TPB, commonly used (although separately) to explain decisions under risk.

Previous papers have combined the health belief model (HBM) and TPB (Bae & Chang 2020, Huang et al., 2020).[2] Instead, our model extends the expected utility model, and is the first of its kind in explaining tourist behavior. We note that the proposed model is not limited to health risks and tourist behavior and that it could be applied to a wide range of risky situations that affect behavior. Second, we extend the concept of subjective norms in TPB to account not only for others' approval of one's decision to travel but also to account for the externality imposed on others by one's behavior. That is, our model allows for individuals caring about the possibility of infecting others. Third, we account for a potential temporal change in leisure tourist behavior in the face of evolving uncertainty by using data collected at different time/waves.

The remainder of the chapter is organized as follows: the Background section provides information and a brief literature review in regard to COVID-19 and its impact on tourism. The Conceptual Modeling section extends the expected utility model to account for subjective norms and perceived behavioral control. The Empirical Modeling section introduces the econometric model (binary logistic regression) used to examine and test travel behavior hypotheses based on the conceptual model. The Data section provides information about data collection, variable construction, and summary statistics. The Results section provides the main results. The Discussion and Conclusion section provides policy implications and our final thoughts.

2.3. Background

As of 2017, the US travel and tourism sector provided 7.8 million jobs and $1.62 trillion in total travel and tourism output, or 2.8% of the country's GDP (NTTO, 2018). Travel disruptions caused by natural disasters, terrorism, and health and safety crises profoundly impact tourism (Ghaderi &

[2] The HBM is centered around the study of health behavioral change and protective actions. For example, HBM models have been widely used to explain sexual behavior (e.g., Champion & Skinner, 2008), vaccination (e.g., Jones et al. 2015), food consumption (Shim & You, 2015), and also tourism and hospitality (Huang et al., 2019; Bae & Chang 2020).

Henderson et al., 2013, Samitas et al., 2018). To curb the spread of COVID-19, lockdowns (in the form of stay-at-home orders) and travel restrictions were implemented worldwide and in about 42 states in the United States since mid-March 2020 (CDC, 2020). In most if not all US states and/or cities within states during 2020, restrictions to various degrees were placed on eating and drinking establishments, sport and entertainment venues, and other hospitality and tourism-based businesses. These measures combined with people's reluctance to travel, stay in hotels, or go out to eat or drink had enormous negative economic impacts on the hospitality and tourism industry. The cumulative loss in the US travel economy[3] since the beginning of March 2020 through the end of the year amounted to $492 billion, resulting in about $64 billion loss in tax revenue at the federal, state, and local levels (US Travel Association, 2021).

The study of health risk perceptions and behavior of individuals regarding travel is important from an economic standpoint, and also for public health reasons as travel poses a threat for the spread of infectious disease (Jonas et al., 2011, Aro et al., 2009, Lopez-Velez et al., 2007). Regarding COVID-19, Gössling et al. (2020) state that there is a need to "understand the behavioral demand responses of tourists in the short- and longer-term." There is also a need to better understand how different types of travelers (e.g., business vs. leisure travelers) perceive and assume health risks (Aro et al., 2009). Several studies have assessed the impact of COVID-19 on the tourism industry (Kaushal & Srivastava, 2020, Gössling et al., 2020, Hoque et al., 2020, Higgins-Desbiolles, 2020, Lee & Chen 2020, Boto-García & Leoni, 2021, Watson & Deller, 2021). Kaushal & Srivastava (2020) examined the challenges facing tourism and hospitality amidst the pandemic and the lessons the tourism industry can learn from COVID-19 conditions. Gössling et al. (2020) examined whether COVID-19 was an "unknowable risk" and assessed the reported

[3] US Travel economy is the contribution of travel and tourism industry to the US economy such as contribution to gross domestic product, employment, and investment.

impacts of COVID-19 on global tourism. Bae & Chang, 2020 used the health belief model (HBM) and an extended theory of planned behavior (eTPB) to examine the impact of risk perception of COVID-19 on behavioral intention towards 'untact' tourism.

2.4. Conceptual Model

We extend the expected utility theory (EUT) model using the theory of planned behavior (TPB) to conceptualize the decision to engage in recreational travel during the COVID-19 pandemic. EUT is the standard "workhorse" model in economics to explain decision making under risk and uncertainty (Kahneman & Tversky, 1979; Shoemaker, 1982; Starmer, 2000; Harrison & Rutström, 2009). Expected utility is measured by weighting the utility of alternative actions with their probabilities. When the outcomes of individual decisions are uncertain, EUT says that individuals will choose the decision that maximizes their expected utility.

Our *baseline model* is exclusively based on the EUT. In our application, the decision of whether to travel for recreation is made in an uncertain context, where traveling provides utility but also increases the probability of getting sick with COVID-19. We define two states C = {C_1 = contract COVID-19, C_2 = do not contract COVID-19} and a set of two actions T = {t_1 = yes, travel, t_2 = no, do not travel/postpone}, where the subjective probability of a state is contingent on the decision to travel; $P\left(C_j \middle| t_k\right)$. Ordinarily, an individual who stays at home has a lesser chance of contracting COVID-19. Therefore, we assume that the probability of not contracting COVID-19 conditional on not traveling, $P(C_2|t_2)$, is greater than the probability of not contracting COVID-19 given traveling, $P(C_2|t_1)$, which in turn is greater than the probability of contracting COVID-19 given traveling, $P(C_1|t_1)$, which is greater than the probability of contracting COVID-19 given not traveling, $P(C_1|t_2)$. That is, $P(C_2|t_2) > P(C_2|t_1) > P(C_1|t_1) > P(C_1|t_2)$ and $0 < P\left(C_j \middle| t_k\right) < 1$. This assumption is based on the premise that COVID-19 spread through the air and individuals are prone to contracting it by being close to someone who has it, and traveling might increase the chances of being around someone with COVID-19. Therefore, an individual who chooses to stay at home (not traveling) is less likely to contract COVID-19 compared to an individual who chooses to travel. Still, we assume that the chances of contracting COVID-19 while travelling are low, although they are higher than the probability of contracting COVID-19 while not travelling.

Total utility is assumed to be additive and to depend on the utility of state j, $U\left(C_j\right)$, and the utility derived from travel, $U(t_k)$, so that $U\left(C_j, t_k\right) = U\left(C_j\right) + U(t_k)$. We assume that the utility derived by an individual in state C_1 "contracting COVID-19" is less than zero ($U(C_1) < 0$), because whether an individual choose to travel or not, there is disutility from being infected with COVID-19, which may lead to sickness and being hospitalized, with even a possibility of death. The utility that an individual gets from state "not contracting COVID-19" is assumed to be greater than zero ($U(C_2) > 0$), regardless of their action to travel or not. Likewise, we assume the utility an individual derives from traveling is greater than zero ($U(t_1) > 0$), indicating that travelers naturally enjoy recreation and leisure travel. Furthermore, we assume the utility of an individual not traveling can be either zero or lesser than zero ($U(t_2) \leq 0$) given the individuals' preference for traveling.

The expected utility can then be written as

$$E[U|t_k] = \sum_{j=1}^{2} P\left(C_j \middle| t_k\right) U(C_j, t_k), \tag{1}$$

where action k = 1: travel, 2: do not travel/postpone, and state j = 1: contract COVID-19, 2: do not contract COVID-19. That is,

$$E[U|t_1] = \sum_{j=1}^{2} P(C_j\,|t_1)U\big(C_j,\ t_1\big) = P(C_1|t_1)U(C_1) + P(C_2|t_1)U(C_2) + U(t_1) \tag{2}$$

and

$$E[U|t_2] = \sum_{j=1}^{2} P(C_j\,|t_2)U\big(C_j,\ t_2\big) = P(C_1|t_2)U(C_1) + P(C_2|t_2)U(C_2) + U(t_2). \tag{3}$$

When deciding whether to go ahead with travel or cancelling/postponing a trip, the individual will compare equations (2) and (3) and cancel/postpone travel when $E[U|t_1]$< $E[U|t_2]$. We note, however, that the signs and magnitudes of $E[U|t_1]$ and $E[U|t_2]$ in equation (2) and (3) are ambiguous, as they depend on the impacts that getting sick or not has on the general utility, on the subjective probability of contracting COVID-19 while traveling, and on the utility derived from travel.

2.4.1. Extended Expected Utility Model

The expected utility model in equations (1) to (3) is a stylized model that highlights how rational individuals would choose between alternative options in a risky situation. In practice EUT can make faulty predictions when, for example, decisions are influenced by the opinions or the welfare of relevant other people in one's life such as family and friends. We hypothesize that, in addition to the risk perception of contracting COVID-19 while traveling, the decision to engage in recreational travel depends on subjective norms and as well as perceived behavioral control. TPB incorporates attitudes, subjective norms, and perceived behavioral control to evaluate intentions to perform a behavior (Ajzen, 1991; Bish et al., 2000). Thus, we extend the EUT model by adding two additional variables: *subjective norms* ($U_{others}(t_k)$), and *perceived behavioral control* (PBC)

from TPB, where $U(t_1)$ is a function of PBC; that is, the utility an individual derives from travel is also dependent on their PBC, $U(t_1|PBC)$. With this extension, equations (2) and (3) become.

$$E[U|t_1] = \sum_{j=1}^{2} P(C_j\,|t_1)U(C_j) + U(\,t_1|PBC) + \;U_{others}(t_1) \tag{4}$$

$$E[U|t_2] = \sum_{j=1}^{2} P(C_j\,|t_2)U(C_j) + U(\,t_2) + \;U_{others}(t_2) \tag{5}$$

In equations (4) and (5), the *subjective norms* term can be positive or negative depending on whether the approval/disapproval of others reinforces or contradicts the individual's decision to travel or not.

Moreover, the effect that the "utility" of others has on an individual's decision to travel, $U_{others}(t_k)$, could be further decomposed into two-parts. The first component is the approval/disapproval of friends and family of the travel behavior itself $U_f(t_k)$ –this is the part accounted for by TPB. The second component (and a contribution of this paper) reflects the negative externality that traveling might have on others in terms of infecting them and increasing community transmission, $U_{infectothers}(t_k)$.

$$E[U|t_1] = \sum_{j=1}^{2} P(C_j\,|t_1)U(C_j) + U(\,t_1|PBC) + U_f(t_1)\; + \;\; U_{infectothers}(t_1) \tag{6}$$

$$E[U|t_2] = \sum_{j=1}^{2} P(C_j\,|t_2)U(C_j) + U(\,t_2) + \;U_f(t_2)\; + \;\; U_{infectothers}(t_2) \tag{7}$$

2.5. Empirical Model

For the empirical application, we assume, as it is common in the literature, that a binary decision (to travel in our case), can be modeled by a sigmoid function, e.g., a logistic function (Harrison & Rutström, 2009, Chakravarty & Roy, 2009). Thus, we estimated a binary logistic regression model:

$$T_{ird} = \frac{exp(Z_{ird})}{1+exp(Z_{ird})} + \varepsilon_{ird}, \tag{8}$$

where T_{ird} is the probability of canceling or postponing travel for individual *i* in region *r* on survey date d. 1 is assigned to individuals who canceled or postponed their trip and 0 otherwise. Z_{ird} is a linear combination of potential determinants of travel.

We estimate two different models. In the baseline model, $Z_{ird} = \alpha + \gamma RP_{ird} + \theta X_{ird} + \eta_r + \eta_{dy}$, where RP_{ird} measures individual risk perception; X_{ird} is a vector of socio-economic variables (age, gender, education, income, race, marital status, having children, employment status); η_r denotes region fixed effects, η_{dy} are day of week dummies, and ε_{ird} is the error term, distributed by the standard logistic distribution. In the more comprehensive model, $Z_{ird} = \alpha + \gamma RP_{ird} + \delta SN_{ird} + \upsilon PBC_{ird} + \theta X_{ird} + \eta_r + \eta_{dy}$, where, in addition, SN_{ird} is the subjective norm (i.e. the utility of relevant others) and PBC_{ird} denotes perceived behavioral control. The relationship between corresponding variables from the conceptual and empirical models is explained within Appendix Table A.1.

2.6. Data

We collected primary data through an online survey administered through Qualtrics, Inc. which was designed to gather information on the impact of COVID-19 on travel sentiment and behavior. The data collection was drawn randomly by Qualtrics, Inc. for a representative sample of the US population covering 48 states. The final sample covers all US states except North Dakota and New Hampshire. Data collection was in two waves: wave 1, from June 23 to July 1, 2020 (about 3 months after the first state in the US declared a mandatory stay-at-home order), with 541 respondents; and wave 2, from October 1 to October 15, 2020, with 913 respondents. Total respondents are thus 1,454 for both waves. Data collection at different time periods during the pandemic allows us to examine travelers' behavioral changes as the severity of the pandemic measured by the total numbers of confirmed cases varies over space and time and as people developed coping strategies over time. It took respondents an average time of approximately 16 minutes to complete the survey.

The description of the variables and the summary statistics are displayed in Table 2.1. To measure *behavioral change*, one question on the survey asked: "For 2020, did you cancel or postpone any recreation or leisure overnight trips throughout the US after learning about the COVID-19 threat?" with answers "Yes-cancel", "Yes-Postpone", "No". 66.44% of the respondents indicated that no, they had not canceled/postponed recreation trips, while 33.56% indicated they had. Figure 2 shows the histogram of the number of canceled trips, indicating that the number of intended recreation trips canceled or postponed in 2020 with highest frequency is 1 trip with 43.54%, while the average number of canceled trips is 2.75.

In order to capture *risk perceptions*, the survey asked: "What is the probability that traveling within the U.S. in the next six months will lead you to: 1. Be around others with COVID-19, 2. Contract COVID-19, 3. Be hospitalized with COVID-19?", with responses on the scale of not probable, somewhat improbable, neutral, somewhat probable, and very probable). In addition, the survey had two questions that allow us to evaluate the relative importance of health and financial risks in the decision of whether to cancel or not travel: *Health Risk* (“in your opinion, how serious do you think the health risks of COVID-19 are to you?”), *Financial Risk* (“in your

Table 2.1: Definition of Variables and Descriptive Statistics

Variable	**Type**	**Description**	**Frequency (%)**		
			Combined Waves (N=1,454)	**Wave 1 (N=514)**	**Wave 2 (N=913)**
Travel Decision	Categorical	For 2020, did you cancel or postpone any recreation or leisure overnight trips throughout the U.S. after learning about COVID-19?			
		Yes-cancel/Yes-postpone	488 (33.56)	194 (35.86)	294 (32.20)
		No	966 (66.44)	347 (64.14)	619 (67.80)
			Mean (std. dev)		
Number of canceled trips	Continuous	Number of intended recreation or leisure trips canceled or postponed in 2020	2.75 (2.99)	2.64 (2.83)	2.82 (3.09)
Risk Perception (*rp*)	Categorical	What is the probability that traveling within the U.S. in the next six months will lead you to? 1=not probable, 2=somewhat probable, 3=neutral, 4=somewhat probable, and 5=probable			
		rp1 - Be around others with COVID-19.	3.056 (1.43)	3.19 (1.42)	2.979 (1.430)
		rp2 - Contract COVID-19.	2.979 (1.38)	3.05 (1.38)	2.94 (1.38)
		rp3 - Be hospitalized due to COVID-19	2.72 (1.37)	2.76 (1.35)	2.697 (1.389)
Subjective Norms (*sn*)	Categorical	Please continue to indicate your level of agreement with the following statements. 1=strongly disagree, 2=Disagree, 3=neutral, 4=Agree, and 5=Strongly agree			3.02 (1.25)
		sn1 - Most people who are important to me think I should travel within the U.S. in the near future.	2.95 (1.28)	2.82 (1.34)	
		sn2 - The people in my life whose opinions I value would approve of me traveling within the U.S. in the near future.	3.09 (1.25)	2.989 (1.28)	3.15 (1.23)
		sn3 - Most people who are important to me would travel within the U.S. in the near future.	3.11 (1.27)	3.03 (1.28)	3.16 (1.27)
Perceived Behavioral Control (pbc)	Categorical	Please indicate your level of agreement with the following statements.			

		1=strongly disagree, 2=Disagree, 3=neutral, 4=Agree, and 5=Strongly agree			
		pbc1 - It is easy for me to travel within the U.S. in the near future.	3.25 (1.24)	3.16 (1.28)	3.31 (1.21)
		pbc2 - Whether or not I travel within the U.S. in the near future is completely up to me.	3.82 (1.09)	3.85 (1.09)	3.80 (1.09)
		pbc3 - If I wanted to, I could travel throughout the U.S. in the near future.	3.68 (1.15)	3.72 (1.16)	3.66 (1.15)
		pbc4 - I have complete control over traveling throughout the U.S. in the near future.	3.61 (1.17)	3.61 (1.18)	3.62 (1.17)
		pbc5 - It is possible for me to travel throughout the U.S. in the near future.	3.62 (1.16)	3.64 (1.17)	3.61 (1.16)
Transmit to others	Binary	1=if concern of inadvertently transmitting COVID-19 to people at the destination or to relatives and friends upon return	0.165 (0.37)	0.181 (0.385)	0.16 (0.363)
Health Risk (hr)	Categorical	In your opinion, how serious do you think the health risks of COVID-19 are to you. 0=Not at all serious/Slightly serious, 1=Moderately serious/very serious/extremely serious	0.72 (0.45)	0.723 (0.448)	0.72 (0.45)
Financial Risk (fr)	Categorical	In your Opinion, how serious do you think the financial risks of COVID-19 are to you. 0=Not at all serious/Slightly serious, 1=Moderately serious/very serious/extremely serious	0.69 (0.46)	0.684 (0.465)	0.7 (0.46)
Variable	**Type**	**Description**		**Frequency (%)**	
Age	Categorical	18-24	260 (17.88)	93 (17.19)	167 (18.29)
		25-29	202 (13.89)	75 (13.86)	127 (13.91)
		30-34	167 (11.49)	46 (8.50)	121 (13.25)
		35-39	165 (11.35)	64 (11.83)	101 (11.06)
		40-44	139 (9.56)	56 (10.35)	83 (9.09)
		45-49	108 (7.43)	37 (6.84)	71 (7.78)
		50-54	98 (6.74)	36 (6.65)	62 (6.79)
		55-59	75 (5.16)	32 (5.91)	43 (4.71)
		60-64	73 (5.02)	31 (5.73)	42 (4.60)
		65-69	89 (6.12)	39 (7.21)	50 (5.48)
		70 and above	78 (5.36)	32 (5.91)	46 (5.04)
Income	Categorical	Under $24,999	361 (24.83)	140 (25.88)	221 (24.21)
		$25,000-$34,999	246 (16.92)	72 (13.31)	174 (19.06)
		$35,000-$49,999	165 (11.35)	71 (13.12)	94 (10.30)
		50,000-74,999	280 (19.26)	91 (16.82)	189 (20.70)
		$75,000-$99,999	173 (11.90)	67 (12.38)	106 (11.61)
		$100,000-$149,999	113 (7.77)	44 (8.13)	69 (7.56)

		150,000 and above	116 (7.98)	56 (10.35)	60 (6.57)
Education	Categorical	Grade school	29 (1.99)	9 (1.66)	20 (2.19)
		High school	447 (30.74)	164 (30.31)	283 (31.00)
		Some Degree	368 (25.31)	127 (23.48)	241 (26.40)
		Associated Degree (2years)	219 (15.06)	92 (17.01)	127 (13.91)
		Bachelor's Degree (4years)	210 (14.44)	74 (13.68)	136 (14.90)
		Graduate Degree (Post Degree/Masters)	181 (12.45)	75 (13.86)	106 (11.61)
Marital Status	Categorical	Married	543 (37.35)	222 (41.04)	321 (35.16)
		Single	542 (37.28)	186 (34.38)	356 (38.99)
		Divorced	139 (9.56)	57 (10.54)	82 (8.98)
		living as married or partnered	151 (10.39)	53 (9.80)	98 (10.73)
		widowed	56 (3.85)	16 (2.96)	40 (3.38)
		Separated	23 (1.58)	7 (1.29)	16 (1.75)
Gender	Categorical	Female	781 (53.71)	293 (54.16)	488 (53.45)
		Male	643 (44.22)	233 (43.07)	410 (44.91)
		Others	30 (2.06)	15 (2.77)	15 (1.64)
Race	Categorical	White	946 (65.06)	397 (73.38)	549 (60.13)
		Black	292 (20.08)	69 (12.75)	223 (24.42)
		Hispanic	72 (4.95)	22 (4.07)	50 (5.48)
		Two or more race	54 (3.71)	21 (3.88)	33 (3.61)
		Asian	48 (3.30)	15 (2.77)	33 (3.61)
		Native Hawaiian	9 (0.62)	3 (0.55)	6 (0.66)
		Others	33 (2.27)	14 (2.59)	19 (2.08)
Employment Status	Categorical	Employed full-time	614 (42.23)	222 (41.04)	392 (42.94)
		Not employed	298 (20.50)	117 (21.63)	181 (19.82)
		Retired	189 (13.00)	83 (15.34)	106 (70.21)
		Employed part-time	216 (14.89)	73 (13.49)	143 (15.66)
		Disable	116 (7.98)	36 (6.65)	80 (8.76)
		Furlong	21 (1.44)	10 (1.85)	11 (1.20)
With Children	Categorical	Do you have children under 18 living at home?			
		No	892 (61.35)	345 (63.77)	547 (59.91)
		Yes	562 (38.65)	196 (36.23)	366 (40.09)

opinion, how serious do you think the financial risks of COVID-19 are to you?”), with responses on a 5-point Likert scale: “not at all serious, slightly serious, moderately serious, very serious, extremely serious” that were recoded into two categories of “not serious” and “serious”.

Subjective norms were assessed based on the level of agreement in a 5-point Likert scale with the following statements: 1. “Most people who are important to me think I should travel within the U.S. in the near future,” 2. “The people in my life whose opinions I value would approve of me traveling within the US in the near future.” 3. “Most people who are important to me would travel within the US in the near future.” The concern of disease transmission, *Transmitting to others*, was

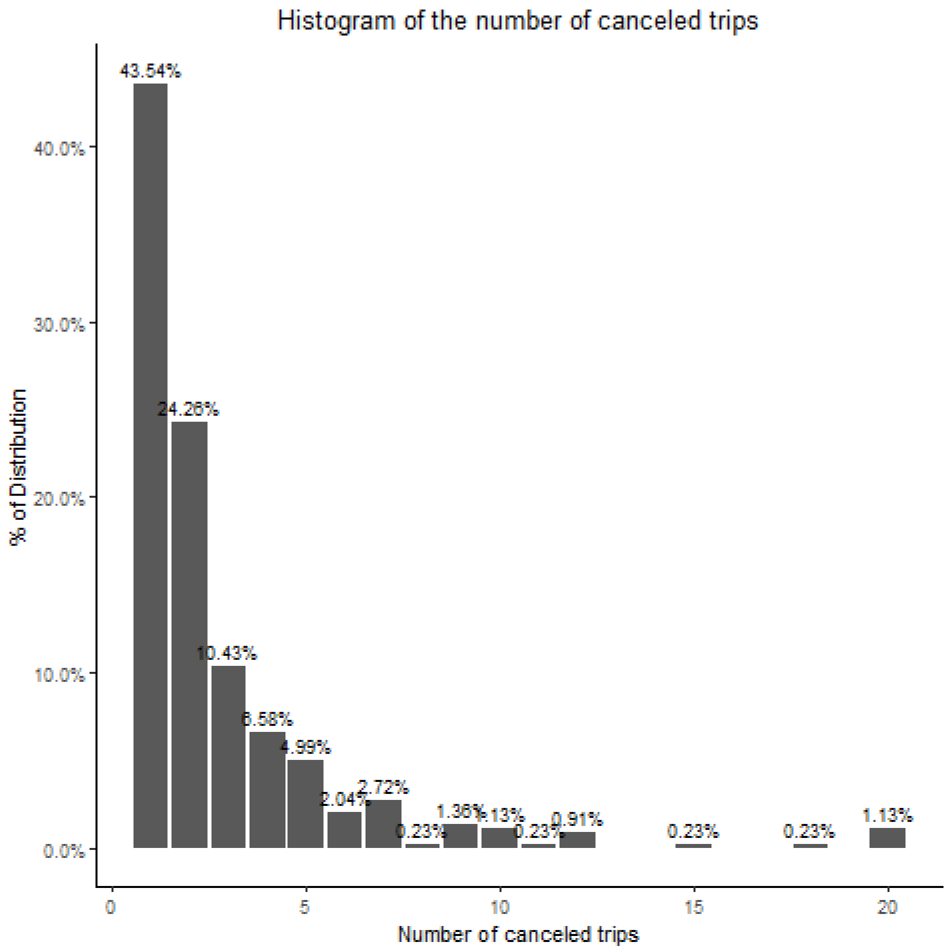

Figure 2.1: Histogram of the number of intended recreation or leisure trips canceled or postponed in 2020.

measured with the yes/no answer to the following question: "In your decision to cancel or postpone your US overnight recreation or leisure trips, which factors played a role?" with "concern of inadvertently transmitting COVID-19 to people at the destination or to relatives and friends upon my return" being an option.

Perceived behavioral control was assessed based on the level of agreement in a 5-point Likert scale with the following statements: 1. "It is easy for me to travel within the US in the near future." 2. "Whether or not I travel within the US in the near future is completely up to me." 3. "If I wanted to, I could travel throughout the US in the near future." 4. "I have complete control over traveling throughout the US in the near future." 5. "It is possible for me to travel throughout the US in the near future."

As it is apparent from the description of the key variables above, for each of the constructs of interest, there are multiple questions that we could use. The answers to those questions are correlated with each other, and Table 2.2 displays the correlation matrix. One way to tackle the correlation while retaining as much information as possible is by converting the data into an index. The most common statistical method to do the decorrelation and reduce the dimensionality of the data is principal component analysis (PCA) (Jolliffe & Cadima, 2016). Therefore, we used PCA for the construct of risk perception, subjective norms, and perceived behavioral control. Values of the Kaiser-Meyer-Olkin (KMO) test (which measures how well suited the data is for factor analysis) provides values of sampling adequacy of 0.67, 0.75, and 0.85, for risk perceptions, subjective norms, and perceived behavioral control, respectively. As a rule of thumb, values above 0.6 indicate the sampling is adequate for PCA (Dodge, 2008).

Table 2.2: Pairwise Correlations of the Key Variables of Interest

Variables	rp1	rp2	rp3	sn1	sn2	sn3	pbc1	pbc2	pbc3	pbc4	pbc5	hr	fr
rp1	1.00												
rp2	0.61	1.00											
rp3	0.51	0.77	1.00										
sn1	-0.05	-0.10	-0.06	1.00									
sn2	-0.09	-0.15	-0.10	0.78	1.00								
sn3	-0.06	-0.14	-0.12	0.74	0.78	1.00							
pbc1	-0.05	-0.14	-0.11	0.55	0.52	0.50	1.00						
pbc2	-0.01	-0.07	-0.09	0.13	0.15	0.15	0.35	1.00					
pbc3	0.01	-0.06	-0.07	0.28	0.29	0.30	0.49	0.54	1.00				
pbc4	-0.03	-0.11	-0.09	0.25	0.27	0.29	0.43	0.56	0.65	1.00			
pbc5	0.02	-0.07	-0.10	0.35	0.36	0.38	0.54	0.47	0.66	0.59	1.00		
hr	0.18	0.30	0.33	-0.18	-0.21	-0.19	-0.22	-0.01	-0.08	-0.02	-0.10	1.00	
fr	0.14	0.21	0.21	-0.06	-0.09	-0.07	-0.10	-0.02	-0.04	-0.04	-0.05	0.54	1.00

This table display the correlation matrix among the key variables of interest *risk perception (rp1 – rp3), subjective norms (sn1 – sn3), perceived behavioral control (pbc1 – pbc5), health risk (hr),* and *financial risk (fr)*. This shows that rp1 to rp3 are highly correlated, sn1 to sn3 are highly correlated, and pbc1 to pbc5 are highly correlated. For definition of the variables, please see Table 2.1.

Other questions on the survey gathered *socio-economic information* (such as age, marital status, or employment). Our sample is slightly younger than the US population (25.38% of respondents are between 25 and 34 years of age, compared to a corresponding 13.9% from the US Census 2019). 65.06% are white; 57.12% are either partially or fully employed, and 53.17% are female. This compares to corresponding US Census figures of 72%, 60.2% and 49.2%, respectively (United States Census, 2019).

2.7. Results

Table 2.3 presents the results from the logistic regression displayed for the EUT baseline model (equations 2 and 3) in column 1, and the extended model (equations 4 and 5) in column 2. The regression coefficients in Table 2.3 represent the marginal effect of the variables of interest.

Equations 6 and 7 were not included in the regression because the variable "*Transmitting to others"* is perfectly correlated with the outcome variable (*travel decision*). Table 2.4 showing the cross tabulation between these two variables indicates that everyone who canceled or postponed their travel was concerned about transmitting COVID-19.

For the baseline model (column 1 Table 2.3), the estimate for risk perception is statistically significant at a 1% level. This indicates that a 1-point increase in respondents' risk perception index leads to a 5.67% increase in the probability to cancel/postpone overnight trips within the US. The wave dummy exhibits a negative sign and statistically significant at 10% suggesting that US residents may have experienced some fatigue from COVID-19, and they are less likely to cancel or postpone leisure travel when asked later in the year (October vs. July 2020) despite the country still being hit by the pandemic. Also, the interaction term of risk perception and wave shows a negative coefficient that is not statistically significant, perhaps because the two survey waves are close together.

Table 2.3: Logistic Regression Result of the Decision to Cancel or Postpone Recreation Overnight Travels Within the U.S.

Dependent variable: Travel Decision VARIABLES	Baseline Model (1)	Risk Types Baseline Model (2)	Extended Model (3)	Risk Types Extended Model (4)
Risk Perception	0.0567***		0.0598***	
	(0.0171)		(0.0175)	
Wave Dummy	-0.0660*	-0.0731**	-0.0672**	-0.0743**
	(0.0337)	(0.0343)	(0.0342)	(0.0341)
Risk Perception x Wave Dummy	-0.0321		-0.0325	
	(0.0231)		(0.0232)	
Health Risk		0.0772**		0.0834**
		(0.0347)		(0.0351)
Financial Risk		-0.0159		-0.0138
		(0.0224)		(0.0223)
Subjective Norms			0.0140***	0.0110**
			(0.00441)	(0.00537)
Perceived Behavioral Control			0.00140	0.000490
			(0.00733)	(0.00736)
Demographic Variables	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes
Day-of-week	Yes	Yes	Yes	Yes
Observations	1,454	1,454	1,454	1,454
Log Likelihood	-815.51116	-822.64279	-814.19051	-821.8631
Pseudo-R-Squared	0.1210	0.1133	0.1224	0.1142
AIC	1637.022	1651.286	1634.381	1649.726
BIC	1652.869	1667.132	1650.227	1665.572

*** p<0.01, ** p<0.05, * p<0.1, Standard errors in parentheses,
The logistic regression outputs in the table are the marginal effect values.
Standard errors are clustered at the region level. All the models control for covariates such as demographic variables (age, income, education, marital status, gender, employment status, children, and race). Also, dummies for region and day-of-week are included, which controls for the unobserved differences across regions and day of the week. Risk perception, subjective norms, and perceived behavioral control variables used in the analysis are the single indices calculated using principal component analysis of the group of questions that provide each variable: rp1-rp3 for risk perceptions, sn1-sn3 for subjective norms, and pbc1-pbc5 for perceived behavioral control. For definition of the variables, please see Table 2.1.

In column 2 we differentiate between different risk types, namely health and financial risks. Health risk is statistically significant at a 5% level with a coefficient of 0.0772. This is an intuitive result indicating that the probability of canceling or postponing leisure travel is larger for individuals who take the health risk of COVID-19 seriously compared to those who do not. In contrast, the financial risk variable is not statistically significant, suggesting that health risks are a more important factor in people's decision to cancel/postpone recreation trips amidst COVID-19. As in column 1, the wave dummy variable is statistically significant at 5%. The interaction variable between the risk perception and wave dummy is not reported here for simplicity as it was not statistically significant (see Appendix Table A.2, column 1 for full set of results).

Column 3 of Table 2.3 shows the estimates of the extended EUT model. In the extended model, we further decomposed subjective norms into two variables; the relevant others' perception and the negative externality on others of traveling (based on equations 6 and 7). As indicated above, however, all those who cancel or postpone recreational travel are concerned about transmitting COVID-19 (Table 2.4). In column 3, *risk perception* is statistically significant at a 1% level, and of comparable magnitude to the estimate in column 1. The coefficient estimates on the subjective norms variable is statistically significant at 1%. It indicates that as the level of agreement with important others approving of them to recreationally travel, their probability of canceling/postponing recreation trips increases by 1.40%. *Perceived behavioral control* (PBC) is not statistically significant suggesting that PBC is not an important reason for canceling or postponing trips in our sample. The Akaike information criterion (AIC) and Bayesian information criterion (BIC) model selection criteria show that the extended model is preferred (Table 2.3). The interactions between the wave dummy and the TPB variables in the extended model (subjective norms, and perceived behavioral control), reported in Appendix A Table A.2 column 2, are not statistically significant.

Finally, column 4 displays the coefficients for risk type. As in column 2, while *health risk* is found to be statistically significant, *financial risk* is not.

Table 2.4: Cross-Tabulation of Transmission Concern and Travel Decision

concern of inadvertently transmitting COVID-19 to people	indicate whether the respondent cancel or postpone any recreation or leisure trip		
	0=No	1=Yes	Total
no	966	248	1214
yes	0	240	240
Total	966	488	1454

2.8. Discussion and Conclusions

This paper shows that risk perceptions and subjective norms are significant factors influencing traveler's decisions to cancel or postpone recreation trips in the US in both June-July 2020 and October 2020. Further investigation into the nature of the travel risks suggests that it is health risks rather than financial risks perception that changed travelers' decisions. This is consistent with Jonas et al. (2011) who found that health risk perception ranks high among other types of risk perception (although their study focuses on tourists traveling to low-income countries). Our finding reflecting the importance of COVID-19 health risk perceptions is consistent with more recent studies on travel intention and vacation travel behavior change during the pandemic (Perić et al., 2021; Bratić et al., 2021; Neuburger & Egger 2020; Falahuddin et al. 2020).

In the way of theoretical implications, our results also indicate that an EUT model extended to incorporate TPB constructs is preferred to the baseline EUT model to explain travelers' behavior during the COVID-19 pandemic. EUT is concerned with individual utilities and subjective probabilities while TPB measures behavioral intention using attitudes, subjective norms, and perceived behavioral control. Our results indicate that both subjective probabilities (those reflecting health risks) and subjective norms affect individuals' decision to travel, while perceived behavioral control does not affect that decision. This last result is consistent with Arikkat & Mohana (2021) and suggests that perceived behavioral control (PBC) may be irrelevant when travel decisions involve elevated health risk, such as with the COVID-19 pandemic. PBC found to be insignificant may be as a result of the health risks. This might be greater than an individual perception of easiness or difficulty to travel for leisure during COVID-19 pandemic. Despite this potential explanation, Aschwanden, Strickhouser, Sesker, Lee, Luchetti, Terracciano, & Sutin (2021) recently found that perceived behavioral control was a significant predictor of individuals' preventative behaviors during the pandemic.

One of the TPB constructs included in the extended EUT model is subjective norms. A large literature in behavioral studies has studied the role of social norms in decision making (Barron, 1992; Bicchieri, 2005; Bicchieri & Xiao, 2009; Tesar, 2020). Bicchierri (2005), categorized social norms into two groups: empirical expectation (what an individual expects others to do) and norm expectation (what we think other expect us to do). The subjective norms considered in our paper are related to norm expectation. In addition, our study considers another element reflecting concern for others' welfare that may be considered more altruistic and people willingness to contributes to a public good (external benefit or positive externality): the concern of transmitting COVID-19 to others in the destination or upon returning from travel. This element proves to be extremely important. Further, all surveyed individuals who canceled or postponed recreational travel were concerned about transmitting COVID-19, which is what Li, Zhang, Liu, Kozak, & Wen (2020) proposed would occur in their recent work concerning tourists' behavioral changes in response to risk perceptions of transmitting COVID-19.

COVID-19 has tremendously affected the hospitality and tourism industry and has underscored that understanding of factors that lead to massive cancelation or postponement of recreational travel is important not only from a public health perspective but also from an economic perspective. Our findings suggest that strategies to influence travelers' subjective norms and health risk perceptions, particularly the concern of infecting others, may be helpful as the recovery from the pandemic is ongoing. One possible strategy would be to enhance destination trust regarding health risks. One example of such actions can be promoting safety measures and precautions of COVID-19 at hotels, restaurants, and tourist attractions (Assaf & Scuderi, 2020). These efforts could take the form of visible postings of standards for social distance, vaccination, and mask requirements on-site at establishments but also on lodging, eateries and bars, and attraction webpages and social media platforms. Such efforts may allay some potential behavioral change and provide visitors with greater peace of mind in deciding to visit.

Application of the proposed model in this study is not limited to the COVID-19 pandemic. Our complementary model uniting EUT and TPB can be tested and applied in additional contexts where tourists are faced with risks and uncertain outcomes in deciding to travel during, for example, other viral disease outbreaks, natural disasters (e.g., floods, hurricanes, wildfires, etc.), times of war and armed conflicts, and terrorism. In each of these contexts, travelers' potential for behavioral change can be examined, especially as we see each of these contexts currently occurring throughout the globe. Furthermore, subsequent research can examine how potential factors affecting U.S. residents' travel decisions evolve over time as we recover from the pandemic, and as vaccines becomes widely available across the country. In so doing, additional model predictors may include potential travelers' vaccine status, perceptions of vaccination, age, response efforts of transportation corporations, availability of health care, established restrictions, and number of those infected with COVID-19 within the destination, etc. Others have offered these constructs as viable predictors within their works (see Chua, Al-Ansi, Lee, & Han, 2020; Parady, Taniguchi, & Takami, 2020; Shamshiripour, Rahimi, Shabanpour, & Mohammadian, 2020, Zhang & Lu, 2021).

Our study does indicate that risk perceptions are an important factor explaining the decision to cancel travel, but that other predictors (such as concern of transmitting COVID 19) cannot be ignored. By extending the expected utility theory with the theory of planned behavior to explain decisions that involve risk (the decision to travel during a pandemic), our study contributes to the to the growing literature on COVID-19, and more broadly to the behavioral and decision-theoretic literature.

2.9. References

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Appendices from Chapter 2: Additional Tables

Table A.1: *Relationship Between Variables in Conceptual and Empirical Models*

Variables in conceptual framework	Explanation	Corresponding variable in empirical model
T	Set of actions: t_1 = yes, travel, t_2 = no, do not travel/postpone	T_{ird} – probability of canceling or postponing travel
$P(C_j\|t_k)$	Subjective probability	RP_{ird} – individual risk perception
U_{others}	Subjective norms (utility of relevant others)	SN – subjective norms (utility of relevant others)
PBC	Perceived behavioral control	PBC – Perceived behavioral control
$U_{infectothers}$	Negative externality of traveling on others	Not included as it is perfectly correlated with dependent variable (travel decision). However, it is shown in a cross-tabulation in Table 3, as “concern of inadvertently transmitting COVID-19 to people”

Table A.2: Logistic Regression Result of the Decision to Cancel or Postpone Recreational Overnight Travels within the United States (Estimate Results with the Full Interaction Variables)

Dependent variable: Travel Decision	Risk Type Baseline Model	Extended Model	Risk Type Extended Model
VARIABLES	(1)	(2)	(3)
Risk Perception		0.0584***	
		(0.0173)	
Subjective Norms		0.000205	-0.00466
		(0.0202)	(0.0192)
Perceived Behavioral Control		0.00683	0.00367
		(0.0132)	(0.0136)
Wave Dummy	-0.0692	-0.0662**	-0.0792
	(0.0574)	(0.0331)	(0.0498)
Risk Perception x Wave Dummy		-0.0301	
		(0.0227)	
Subjective Norms x Wave Dummy		0.0249	0.0279
		(0.0324)	(0.0339)
Perceived Behavioral Control x Wave Dummy		-0.0106	-0.00654
		(0.0127)	(0.0126)
Health Risk	0.0620**		0.0582***
	(0.0268)		(0.0208)
Financial Risk	0.00320		0.00899
	(0.0417)		(0.0453)
Health Risk x Wave Dummy	0.0238		0.0387
	(0.0309)		(0.0469)
Financial Risk x Wave Dummy	-0.0304		-0.0321
	(0.0757)		(0.0791)
Demographic Variables	Yes	Yes	Yes
Region	Yes	Yes	Yes
Day-of-week	Yes	Yes	Yes
Observations	1,454	1,454	1,454
Log Likelihood	-822.51888	-813.29219	-820.60713
Pseudo-R-Squared	0.1135	0.1234	0.1155
AIC	1651.038	1632.584	1647.214
BIC	1649.383	1648.431	1663.06

*** p<0.01, ** p<0.05, * p<0.1, Standard errors in parentheses,
The logistic regression outputs in the table are the marginal effect values.
Standard errors are clustered at the region level. All the models control for covariates such as demographic variables (age, income, education, marital status, gender, employment status, children, and race). Also, dummies for region and day-of-week are included, which controls for the unobserved differences across regions and day of the week. Risk perception, subjective norms, and perceived behavioral control variables used in the analysis are the single indices calculated using principal component analysis of the group of questions that provide each variable.

CHAPTER 3

AUGMENTING RECREATIONAL DEMAND MODELS WITH SUBJECTIVE NORMS [4]

[4] Ojo, K. E., Ferreira, S., Salazar, J., Bergstrom, J., & Woosnam, K. M. To be submitted to *Environmental and Resource Economics.*

3.1 Abstract

This study develops a conceptual model to explain the effects of subjective norms on non-market commodity valuation. Specifically, we empirically test the effects of subjective norms on the change in the willingness to pay for recreation/leisure commodities in the state of Georgia induced by the COVID-19 pandemic, using a travel cost recreation demand model. Survey data collected among U.S. residents in three waves (June–July 2020, October–November 2020, and August 2021) was analyzed using a travel cost recreation demand model fitted with Poisson, negative binomial, random effects Poisson, and random effects negative binomial count data models. The results suggest that subjective norms are a statistically significant recreation demand shifter. Furthermore, we estimate a net decrease of approximately 1,800 in consumer surplus (CS) or willingness to pay (WTP) for visitors to Georgia associated with COVID-19.

Keywords: recreation demand, subjective norms, consumer surplus, COVID-19 pandemic, travel cost model

3.2 Introduction

The loss in welfare from trip cancellations and postponement due to COVID-19 is perhaps an overlooked, hidden cost of the pandemic. Pandemic restrictions such as closures of hotels, restaurants, parks, and other tourist attractions meant fewer recreational commodities available for those tourists who chose to travel during the pandemic, and many decided to cancel planned recreational trips, leading to a welfare loss. Estimating the loss of welfare in the context of COVID-19 requires considering subjective norms because COVID-19 is an infectious disease and engaging in travel has social implications such as increasing the risk of transmission.

The loss in welfare of recreational commodities has been researched extensively in the literature through several methods, including the stated and revealed preferences approach (Bergstrom et al., 1990; English et al., 2018; Habb & McConnell, 2002; Landry et al., 2021; Loomis et al., 2001; Parsons, 2017; Whitehead et al., 2018). In revealed preference approaches or methods, variables such as travel cost, income, risk perception, the price of substitute goods, and socioeconomic variables (e.g., age, education, gender, and race) are often used to explain tourists' preferences[5]. Both attitudes and perceived behavioral control (from the theory of planned behavior [TPB]) have been accounted for in recreational trip demand models and other nonmarket commodity valuations. Specifically, past studies have explored individual subjective risk attitudes and perceptions as well as perceived behavioral control with a focus on individual income in recreational trip demand. Accounting for subjective norms may allow researchers to measure recreation demand more accurately. Therefore, in this study, we developed a conceptual model of

[5] For instance, Landry et al. (2021) utilized risk perception, socioeconomic variables, and travel costs to explain the impacts of COVID-19 on outdoor recreation in the United States. Whitehead et al. (2018) used travel costs, the price of substitute goods, income, and quality of sites to estimate recreational losses from an oil spill. English et al. (2018) used travel cost and socioeconomic variables to assess lost shoreline recreation. Loomis et al. (2001) estimated the effects of fire on recreation demand through travel cost, demographic variables, income, time budget, trail characteristics, and fire characteristics.

the effects of subjective norms on environmental commodity (i.e., recreation/leisure commodity) demand and values expressed through individuals' willingness to pay (WTP) and empirically tested these effects through the revealed preference approach.

While previous studies have used numerous variables with the revealed preference technique, to the knowledge of the authors, this is one of the first studies to consider subjective norms in examining tourists' revealed preference in their trip-taking behavior. Subjective norms are an individual's perception of others' attitudes toward the former engaging or disengaging in a particular behavior, i.e., the predispositions, either positive or negative, of family or friends towards their behavior (Ajzen, 1991; Bae & Chang, 2020; Ojo et al., 2021). Subjective norms are essential to include in a recreation model because they account for sociopsychological factor in tourist decision-making. To this end, Ajzen (1985) proposed TPB, in which an individual's actual behavior can be measured and predicted from intentions. Three variables are often used to explain behavioral intention: attitude, perceived behavioral control, and subjective norms. Attitude toward a behavior is an individual's positive or negative valuation of performing a target action (Ajzen, 1991), while perceived behavioral control is how individuals perceive their capability (such as time or money) to perform a particular action (Bae & Chang, 2020).

The conceptual framework developed for this study models the effects of subjective norms on recreation demand and values. This framework builds on Bergstrom et al.'s (1990) study of the effects of information on environmental commodity valuation decisions. While Bergstrom et al. (1990) tested their empirical study framework with a stated preference approach, we used a revealed preference approach. The conceptual model showed that the effects of subjective norms on recreation/leisure demand and values should be considered on a case-by-case basis. Our empirical analysis focused on using the travel cost method to 1) test the effects of subjective norms and other explanatory variables on tourists' decisions to cancel recreation/leisure trips to the U.S. state of Georgia during the COVID-19 pandemic and 2) estimate the economic value or WTP of tourists who canceled recreation/leisure trips. Georgia tourists were considered in our case study because of the significant contributions of tourism to the Georgia state economy and the negative impact of COVID-19 on this sector. The impact of the COVID-19 on the tourism consumer and the state economy, as well as full details on the rationale for choosing Georgia tourists, are provided in the case study section.

Our empirical analysis was based on primary data collected online for actual and potential Georgia visitors. Explore Georgia, the tourism division of the Georgia Department of Economic Development, provided a list of email addresses for people who had visited Georgia in the past and those who had requested state tourism information. We randomly selected email addresses from this list to be part of a sample of visitors to whom we sent a Qualtrics recreation/tourism survey link. The survey conducted in three waves (i.e., in June–July, October–November 2020, and August 2021), asked respondents about actual and canceled/postponed day and overnight recreation/leisure trips to Georgia before and during the COVID-19 pandemic. We collected 2,886 responses in the three waves. The survey data was used to estimate a recreation demand model through the travel cost model, which we empirically analyzed using Poisson, negative binomial, random effects Poisson (RE-Poisson), and random effects negative binomial (RE-negative binomial) models. We estimated a net decrease of approximately 1,800 in consumer surplus (CS) or WTP for visitors to Georgia associated with COVID-19. Subjective norms were also found to have a positive and statistically significant effect on recreation/leisure demand and net economic value, indicating that subjective norms are potential demand shifters that should be considered in non-market commodity valuation.

The paper contributes to the literature on recreation demand models by examining sociopsychological factors that impact leisure/recreational trip-taking behavior. Specifically, we examined the effects of subjective norms on recreation/leisure trip demand and values. Previous studies have extensively analyzed the TPB and WTP for environmental goods (Ajzen & Driver, 1992; Bernath & Roschewitz, 2008; Cooper et al., 2004; Huang et al., 2014; Jeon et al., 2022; López-Mosquera, 2016; López-Mosquera & Sánchez, 2012; López-Mosquera et al., 2014; Meleddu & Pulina, 2016)[6]. Some of these studies used the TPB solely to explain WTP for the environmental goods in a contingent valuation manner; they treated WTP as behavioral intention and focused only on the psychological factors. Although most of these studies focused only on contingent valuation, they also used exploratory analysis (an empirical estimation) for their estimates.

Additionally, these studies accounted only for psychological factors, but not other explanatory factors commonly used in nonmarket valuation. Moreover, they included all the psychological factors in TPB (attitude, perceived behavioral control, and subjective norms) in their estimation, some of which are partially accounted for by other variables in conventional nonmarket valuation techniques but which they did not include—for example, perceived behavioral control can be explained in terms of time and income, while attitude can be explained through risk perception. Therefore, the study presented in this paper contributes to the traditional nonmarket valuation technique in the environmental economics literature in four ways. First, we focused on revealed preference techniques rather than the stated preference (i.e., contingent valuation) used

[6] Most of these studies focused mainly on estimating psychological factors using the TPB to explain WTP for ecotourism (Maledu & Pulina, 2016); urban, suburban, and nature-based public parks (Huang et al., 2014; López-Mosquera & Sánchez, 2012; López-Mosquera et al., 2014); urban forest (Bernath & Roschewitz, 2008); and change in water quality (Cooper et al., 2004). Ajzen and Driver (1992) treated WTP for environmental goods as a behavioral intention and used the TPB to explain the meaning of contingent valuation measures.

in the previous literature. Second, we developed a conceptual framework for how subjective norms impact WTP. Third, we empirically estimated WTP using an economic approach in nonmarket valuation while accounting for subjective norms instead of the three psychological variables and also for other explanatory variables, such as travel cost, risk perception, and socioeconomic variables. Fourth, our estimation was based on COVID-19 related issues that are crucial during this phase.

The remainder of this chapter is organized as follows. The next section presents the conceptual model of the effects of subjective norms on recreation/leisure demand values (or WTP). Data collection through a survey of visitors to the state of Georgia is then described. Next, the empirical model and data analysis are explained. Estimation results and sensitivity analysis are then presented. Finally, the implications of the study results and conclusions are discussed.

3.3 Conceptual Model

Subjective Norms and WTP

In this paper, we focus on the effects of subjective norms on demand and the value of changes in recreation/leisure commodities. Subjective norms refer to the perception of other people's approval (e.g., family, friends) of an individual's particular behavior (Ajzen, 1991). Consumer surplus or WTP for a change in a recreation/leisure commodity q (which can be a decrease or increase in change) is estimated by the Hicksian demand function $h[p, q, u]$—a function of prices and utility (Bergstrom et al., 1990; Brookshire et al., 1980). Indirect utility (u) is the utility obtained by the individual given p, q, and I, conditional on the individual’s subjective norms (sn).

$$u = v(p, q, I | sn) \tag{1}$$

where p is the nonrationed price vector for the recreation/leisure commodity, q is the rationed recreation/leisure commodity, I is the income, and u is the indirect utility.

The individual's Hicksian demand function is then given by:

$$h[p, q, v(p, q, I|sn) \tag{2}$$

Using (3), we can then derive the individual's WTP for recreation commodity as:

$$\begin{aligned} WTP &= h[p, q^b, v(p, q^b, I|sn) \\ &\qquad - h[p, q^b, v(p, q^a, I|sn)] \\ &= h[p, q^b, v^b] - h[p, q^b, v^a] \\ &= k^o - \ k^1 \end{aligned} \tag{3}$$

where q^a is the subsequent rationed quantity of the recreation/leisure commodity, q^b is the initial rationed quantity of the recreation/leisure commodity, k^o is the initial income level, and k^1 is the subsequent income level. v^a is the indirect utility given price, subsequent quantity, and income, while v^b is the indirect utility given price, initial quantity, and income.

If there is a decrement in the quantity of recreation commodity, assume $q^a - q^b$ in the rationed recreation/leisure commodity from an initial quantity q^1 to a subsequent quantity q^2, where $q2 < q1$. In this case, $q^a = q^1$ and $q^b = q^2$, which implies that Equation (3) is a Hicksian welfare measure connected with the decrement. However, if there is an increment in the quantity of recreation commodity, assume $q^a - q^b$ in the rationed recreation/leisure commodity from an initial q^1 to a subsequent quantity q^2, where $q^2 > q^1$ in this case $q^a = q^2$ and $q^b = q^1$, which implies that Equation (3) measures a Hicksian welfare measure related to the increment.

Intuitively, the rationed recreation/leisure commodities available to tourists pre-COVID were higher than post-COVID in 2020 because of the pandemic restrictions such as hotel, restaurant, park, and other tourist attraction closures. Thus, tourists who chose to travel during the pandemic had fewer recreation/leisure commodities available.

The partial derivative of (4) with respect to *sn* shows the effect of the subjective norms on WTP:

$$\frac{\partial WTP}{\partial sn} = \frac{\partial h}{\partial v^a}\frac{\partial v^a}{\partial sn} - \frac{\partial h}{\partial v^b}\frac{\partial v^b}{\partial sn} \qquad (4)$$
$$= f^a \frac{\partial v^a}{\partial sn} - f^b \frac{\partial v^b}{\partial sn}$$

where the marginal cost of utility are f^a given q^a and f^b given q^b, which are simply the inverses of the marginal utility of money. Equation (4) assumes sn as a variable, implying that the effect of sn on WTP depends on the differential impact of subjective norms on the initial and subsequent utility levels. Assessment of this differential effect is facilitated by expressing WTP as:

$$WTP = \int_{q1}^{q2} - [\frac{dh}{dq}]\, dq \qquad (5)$$

$$= \int_{q1}^{q2} - [\frac{\partial h}{\partial q} + \frac{\partial h}{\partial v}\frac{\partial v}{\partial q}]\, dq$$
$$= -\int_{q1}^{q2} \left[h_q + f(sn)v_q(sn)\right] dq$$

where $f(sn)$ is the marginal cost of utility given sn, and $v_q(sn)$ is the marginal utility of the rationed environmental commodity given sn. The partial derivative of (5) with respect to *sn* shows the differential effects of subjective norms on WTP:

$$\frac{\partial WTP}{\partial sn} = -\int_{q1}^{q2} [\frac{\partial f(sn)}{\partial sn} v_q(sn) + f(sn)\frac{\partial v_q(sn)}{\partial sn}]\, dq \quad (6)$$

The first part of Equation (6) shows the effects of sn on the marginal cost of utility, while the second part indicates the impacts of sn on the marginal utility of the rationed recreation/leisure commodity. Thus, the differential effects of sn on initial and subsequent utility level are given by the changes in $v_q(sn)$ and $f(sn)$, which are caused by the impacts of subjective norms. The direction of the differential effects cannot be stated *a priori*, given the ambiguity of the effects of subjective norms on initial and subsequent utilities and other factors. Thus, the effects of subjective norms on WTP need to be examined empirically on a case-by-case basis. For example, whether subjective norms encourage or discourage the use of a recreation/leisure commodity will yield different results.

We incorporate intuition in the effects of subjective norms on WTP in the context of COVID-19 conceptual framework above. Given the high-risk perception of COVID-19, we hypothesized that subjective norms, in our case, would encourage tourists to cancel/postpone intended or planned trips. The effects of subjective norms on individual behavior regarding recreational travel may have resulted in tourists perceiving that more utility was provided by the pre-COVID-19 state, which implies that $f(sn)$ would decrease because tourists would experience a loss in utility post-COVID-19 when they conform to their subjective norms. Thus, $\frac{\partial v_q(sn)}{\partial sn}$ in Equation (6) will be negative, and the second part of Equation (6) will also be negative because $f(sn)$ is negative. The first part of Equation (6) being negative implies that subjective norms' effect would reduce WTP (consumer surplus). Therefore, one possible effect of subjective norms is to lower the marginal utility of $q,$ which would reduce WTP for recreation/leisure trips. The reduction in a trip's net economic value (or WTP) would then encourage tourists to cancel or postpone recreation/leisure trips due to COVID-19, as depicted in the recreation demand model shown in Figure 3.1. When evaluating the recreation demand model, if we do not consider subjective norms, the demand curve is estimated at D0 in Figure 3.1; however, if subjective norms are included, the demand function decreases to D1. Therefore, we perform a one-tailed test, given as:

$$H^{o}: WTP(Psn) = WTP(Asn)$$

$$H^{a}: WTP(Psn) < WTP(Asn)$$

The null hypothesis H^{o} considers the case in which the WTP is the same in the presence (Psn) or absence (Asn) of subjective norms in estimating the recreation demand model. In contrast, the alternative hypothesis H^{a} states that the WTP estimate in the presence of subjective norms in the recreation demand model is smaller than the WTP estimate in the absence of subjective norms among tourists to Georgia amid the COVID-19 pandemic.

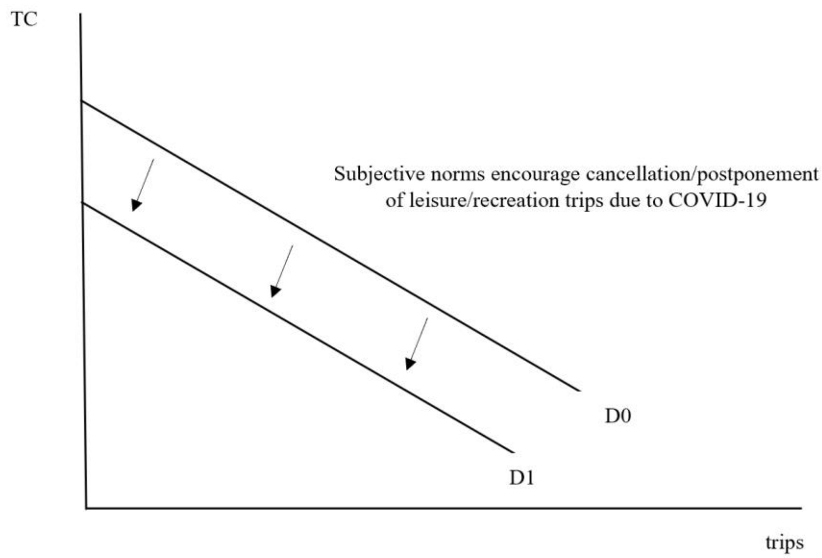

Figure 3.1: Shift in recreation demand due to the addition of the socio-psychological factor (*subjective norms*) while holding other demand shifters constant.

A Case Study

In 2018, the state of Georgia welcomed 111.7 million domestic and international visitors (Explore Georgia, 2020). In 2019, visitor spending increased by 5.9% compared to 2018, whereas in 2020, visitor spending declined by 31% (or approximately $9.5 billion) compared to 2019. This reduction in visitor spending was due to the COVID-19 pandemic. The spread of COVID-19 across the United States in the beginning of March 2020 led to several states issuing stay-at-home orders to curb the spread of the disease. Specifically, Georgia issued a stay-at-home order between March 23, 2020, and April 7, 2020 (Moreland et al., 2020). This order subsequently reduced the total number of visitors to Georgia during 2020, and most of the eventual Georgia tourists in 2020 were in-state residents (Explore Georgia, 2020).

We empirically tested the effects of subjective norms on the demand and value of recreation/tourism trips by analyzing data from potential tourists who planned to visit Georgia but canceled/postponed their leisure/recreation trip due to the COVID-19 threat. The net economic value of canceled trips was estimated by WTP, which is the Hicksian welfare measure defined by Equation (3), where the initial quantity of recreation/leisure commodities available pre-COVID is $q^a = q^1$ and the subsequent level available post-COVID is $q^b = q^2$.

3.4 Survey Information

The survey was conducted online via Qualtrics. Survey links were sent to the email addresses of actual and potential Georgia visitors provided by Explore Georgia, a division of the Georgia Department of Economic Development charged with tourism research and management. The intent of the survey was to collect data on sentiments and behavior related to the COVID-19 pandemic, travel, and tourism.

To obtain information on behavioral change for the different types of trips, i.e., day or overnight trips, the survey asked two yes/no questions: First, “In the last 18 months did you take any DAY TRIPS without staying overnight to the state of Georgia or within Georgia for the primary purpose of recreation or leisure?” If the answer was “yes”, a follow-up question asked: “How many DAY TRIPS did you take to or within Georgia in the last 18 months for the primary purpose of recreation or leisure? If you do not remember exactly, an approximation is okay.” These questions were asked about overnight trips as well: “In the last 18 months, did you take any OVERNIGHT TRIPS to or within the State of Georgia for the primary purpose of recreation or leisure?” If the answer was “yes”, a follow-up question was asked about the number of overnight trips. To ascertain behavioral change during COVID-19, another question asked, “From the start of 2020 to now, how many intended Georgia day trips did you cancel or postpone because of the COVID-19 threat?” The other question asked, “From the start of 2020 to now, did you cancel or postpone any recreation or leisure Georgia overnight trips?” with the possible responses “Yes-Cancel,” “Yes-Postpone,” and “No.”

Three items addressing subjective norms were presented as follows: “Please continue to indicate your level of agreement with the following statements on a 5-point Likert scale from *strongly agree* to *strongly disagree*: ‘Most people who are important to me think I should travel within the U.S. in the near future,’ ‘The people in my life whose opinions I value would approve of me traveling within the U.S. in the near future,’ and ‘Most people who are important to me would travel within the U.S. in the near future.’ Three items concerning COVID-19 subjective risk probabilities were presented using the root, “What is the probability that traveling within the U.S. in the next six months will lead you to” with responses on a 5-point Likert scale from *not probable* to *very probable*. The three items were worded as follows: “Be around others with COVID-19,” “spread COVID-19,” and “be hospitalized due to COVID-19.” Socioeconomic and demographic questions were also asked in the survey, including income, age, gender, and income. The survey also collected information on *travel party* by asking the following question separately for both day and overnight trips: “Including yourself, on average how many people were you going to be financially responsible for during your trips?”

The survey was conducted in three waves: wave 1 from June 25 to July 28, 2020, wave 2 from October 19 to November 17, 2020, and wave 3 from August 16 to August 24, 2021. The total number of usable responses across the three waves was 2,886. As shown in Figure 3.2, respondents were divided into two groups: Group 1 corresponded to actual Georgia visitors who have previously taken trips (pre-COVID) to Georgia, took trips to Georgia during COVID-19, or canceled trips to Georgia due to COVID-19 (past visitors); Group 2[7] corresponded to potential Georgia visitors who had not taken trips to Georgia before COVID-19 but had canceled trips to Georgia due to COVID-19. Respondents who took trips to Georgia during COVID-19 and had canceled trips as past or potential visitors comprised the post-COVID category, while those who took trips to Georgia before the pandemic made up the pre-COVID category. Further, respondents who took trips to Georgia 18 months before wave 1 and 2 surveys were placed in the pre-COVID category, while respondents who took trips to Georgia 18 months before wave 3 surveys were placed in the post-COVID category because the trips were taken during COVID-19 (*taken trips*). Additionally, respondents in waves 1, 2, and 3 who were past visitors and had canceled trips due to COVID-19 were placed in the post-COVID category (*canceled trips*). Likewise, respondents in waves 1, 2, and 3 surveys who were potential visitors and had canceled trips due to COVID-19 were placed in the post-COVID category (*canceler only*).

The empirical analysis was conducted for Group 1 only to assess revealed preferences and WTP values for actual trips taken by respondents before the COVID-19 pandemic. We combined Groups 1 and 2 in another analysis to assess revealed preferences and WTP values for both actual and potential Georgia visitors.

[7] Group 2: respondents who had not taken prior recreation/leisure trips to Georgia but had canceled planned trips due to COVID-19 across the three waves; the canceled trips could have been their first trip to Georgia.

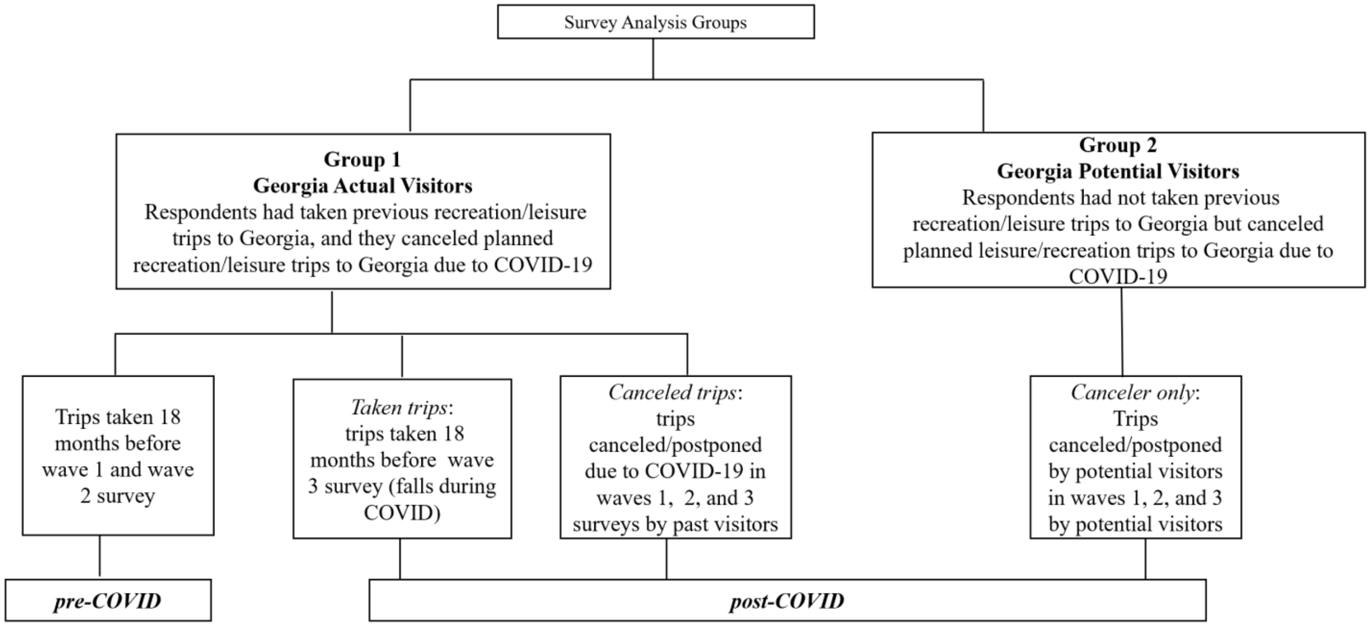

Figure 3.2: Survey analysis groups.

3.5 Travel Cost Model

We used a recreation demand model to test the effects of subjective norms on WTP and to estimate the economic loss experienced by tourists who planned to visit Georgia but canceled/postponed their recreation/leisure trip due to the COVID-19 pandemic. In the literature, the revealed preference technique commonly used to estimate recreation demand is the travel cost method (TCM) because of its ability to model recreational trip behavior in a manner consistent with economic theory and expectations (Bowker & Leeworthy, 1998; Bowker et al., 2007; Bowker et al., 2009; Englin et al., 2001; Haab & McConnell, 2002; Landry et al., 2021; Loomis et al., 2001; Parsons, 2017). Canceling an intended or planned trip is a form of revealed behavior. Therefore, we used the TCM to model a representative tourist's actual and canceled/postponed leisure/recreation trip behavior and to estimate the average individual net economic value (or consumer surplus or WTP) for actual and canceled leisure/recreation trips to Georgia amid the pandemic.

To estimate a TCM demand function, we first needed to calculate the travel cost TC_{ij} of each respondent traveling from their home origin i to the city/town in Georgia j. Travel cost was grouped into monetary and opportunity cost of travel (i.e., the value of time spent traveling). The travel cost estimation included computing the distance traveled from the zip code of the respondent's origin to the city/town in Georgia they intend to visit. Given that the respondents travel from origins across the United States to Georgia, the distance traveled can be considerable.

Following English et al. (2018), we assumed that tourists traveled to Georgia both by driving personal or rental vehicles and/or flying on commercial airlines. We assumed automobile travel costs for all respondents living in Georgia because the maximum one-way traveling distance is under 500 miles. In addition, we assumed that other respondents with one-way driving distances under 500 miles traveled by car to their destination. We further assumed that respondents with one-way driving travel distances above 500 miles traveled by car and by air and split driving and flying costs as follows:

$$TC_{ij} = (1-\rho)TC_{ij}^{D} + \rho TC_{ij}^{F} \tag{7}$$

$$TC_{ij}^{D} = \frac{c_d d_{ij}}{tp} + (\delta \times \frac{I_{ij}}{w_{ij}} \times t_{ij}) \tag{8}$$

$$TC_{ij}^{F} = TC_{ij}^{D}(origin, airport) + C_{parking} + C_{flight} + C_{carrental} + TC_{ij}^{D}(airport, city) \tag{9}$$

where TC_{ij} is the total travel cost of traveling from respondents' origin i to the destination j. TC_{ij}^{D} and TC_{ij}^{F} are, respectively, the driving and flying cost of individual respondents from their home i to city/town in Georgia j, and ρ is the share of respondents flying to city/town j in Georgia. c_d is the average cost per mile, which is the operating cost (e.g., gas, maintenance, tires for a medium-sized car, which is 0.1787/mile in 2020 [American Automobile Association, 2020]. A medium-sized car was assumed because the average group size from the survey data was 2.45. d_{ij} is the round-trip distance travel from respondents' home i to city/town in Georgia j. We used Google API to geocode the intended destination and estimate the distance each respondent traveled from their home (zip code) to the city/town in Georgia. tp is the average travel party size. δ is the opportunity cost of time, given as the standard 33% of the average wage rate[8] (Cesario, 1976; Parsons, 2017). I_{ij} is the household income of the survey respondents. w_{ij} is the number of hours worked assuming a standard 40 hours of work per week. The total number of weeks in a year is 52; thus, the total hours worked per year is 2,080. t_{ij} is the driving time from respondents' origin i to destination j. $TC_{ij}^{D}(origin, airport)$ is the driving cost from the respondent's home to the origin airport, and $TC_{ij}^{D}(airport, city)$ is the driving cost from the destination airport to the site within Georgia. $C_{parking}$ is the cost of parking a car at the airport of origin. C_{flight} is the cost of a flight from the origin airport to the destination airport, and $C_{carrental}$ is the cost of renting a car throughout the trip; more details on the flying cost are provided in Appendix A.

The share of the probability of respondents flying was based on responses from the survey for those who stated that their most comfortable primary mode of transportation to utilize for recreation or leisure is commercial airlines. These probability shares are presented in Table 3.1.

[8] The opportunity cost of time accounts for the disutility of driving time.

Table 3.1: Respondent Share of Flying

	$\text{HHI} \leq \$60k$, Party Size ≤ 2	$\text{HHI} > \$60k$, Party Size ≤ 2	$\text{HHI} \leq \$60k$, Party Size > 2	$\text{HHI} > \$60k$, Party Size > 2
<500	0	0	0	0
>500	0.082	0.301	0.014	0.103

HHI is the annual household income before taxes, while party size is the number of people in the travel party.

We tested the subjective norms hypothesis (H^0) stated above by estimating a travel cost model without *subjective norms (sn)* as shown in Equation (10a) and a travel cost model with *subjective norms (sn)* as shown in Equation (10b),

$$trips_n = f(TC_n, rp_n, tp, sv_n, oth) + \mu \tag{10a}$$

$$trips_n = f(TC_n, sn_n, rp_n, tp, sv_n, oth) + \varepsilon \tag{10b}$$

Given that COVID-19 involves a level of risk when traveling, we also included a *risk perception* (rp) variable in (10a) and (10b). Socioeconomic variables such as income, age, and gender were included in the model. In (10a) and (10b), the $trips$ variable is the number of Georgia day and overnight actual and canceled/postponed trips for individual *n*[9], TC is the travel cost for individual *n*, sn is the subjective norms for individual *n*, rp is the risk perception for individual *n*, tp is the travel party size, and sv is the vector of socioeconomic variables including income, age, gender of individual *n* and whether they were traveling with children. oth is a vector that might

[9] Actual and canceled trips were combined following Landry et al.'s (2021) study, based on the rationale that valuing canceled/postponed trips due to COVID-19 entails accounting for taken trips and canceled trips associated with COVID-19. In addition, the study by Whitehead et al. (2018) is one of the first to combine a revealed preference survey and data on canceled trips to estimate the loss of recreational use value due to the Deepwater Horizon oil spill in the Gulf of Mexico. Thus, combining revealed preference survey data on recreational trips taken and data on canceled trips allows the estimation of the loss in welfare related to canceled trips due to COVID-19 in pre- and post-analysis fashion.

consist of a dummy variable indicating the wave of data collection, μ and ε are considered as the random error.

3.6 Empirical Estimation

In Equations (10a) and (10b), the dependent variable is a nonnegative integer, count data. The Poisson model has been widely used and accepted in evaluating recreation demand functions with count data (Haab & McConnell, 2002; Landry et al., 2021; Loomis et al., 2001; Loomis et al., 2006; Pradhan & Leung, 2006; Wooldridge, 2010). Most of the Poisson models estimated in previous studies have used a semi-log specification, which we also adopted for our data analysis. The general semi-log specification is

$$\lambda = \exp(\beta z), \qquad (11)$$

where λ is the expected value of any Poisson random variable, and z includes TC, sn, rp, tp, sv, oth. β is the coefficient of the parameters to be estimated. One of the problems of using the Poisson distribution is the problem of overdispersion: The Poisson distribution assumes that the mean is equal to the variance, but with actual recreation trip data, sometimes the variance is greater than the mean. In this case, the negative binomial model, which accounts for overdispersion, is more appropriate than the Poisson model. The maximum likelihood method was used for model estimation. In addition, to account for unobserved individual heterogeneity, we also considered an RE-Poisson model and a RE-negative binomial model. The standard errors were clustered at the household level for all models except for the RE-negative binomial model, which does not support a standard error cluster, and standard errors were estimated by the bootstrap method.

The final empirical model is the log-linear form of Equation (10a), and (10b) is specified as:

$$ln(trips) = \beta_1 + \beta_2 TC + \beta_3 rp + \beta_4 tp + \beta_5 Overnighttrips + \beta_6 Income \qquad (12a)$$
$$+ \beta_7 Female + \beta_8 WithChildren + \beta_9 PostCOVID + \beta_{10} Wave + \mu$$

$$ln(trips) = \beta_1 + \beta_2 TC + \beta_3 rp + \beta_4 sn + \beta_5 tp + \beta_6 Overnighttrips + \beta_7 Income \qquad (12b)$$
$$+ \beta_8 Female + \beta_9 WithChildren + \beta_{10} PostCOVID + \beta_{11} Wave + \mu$$

The definition of $trips$, TC, sn, rp, tp, μ remains the same for individual n as explained in the travel cost model framework above. A dummy for overnight trips is included to account for trip type because we considered both day and overnight trips in the estimation. Socioeconomic variables in the model include income; females, with children, dummy indicating; post-COVID; and survey data collection wave.

The consumer surplus or WTP, which is the net economic value for actual and canceled/postponed recreation trips to Georgia, was estimated using $-1/\beta_2$ (Haab & McConnell, 2002; Parsons, 2017). The annualized consumer surplus pre- and post-COVID were estimated using the following:

$$WTP_h = CS_h = \frac{m_h * (\frac{12}{\bar{t}})}{\beta_2} \qquad (13)$$

where h = pre-COVID or post-COVID, and m_h is the mean of trips in period h, which is a scale by $12/\bar{t}$ to annualize the WTP and account for differences in count exposure (Landry et al. 2021). $\bar{t}$ is calculated based on pre- and post-COVID computed in Figure 3.2 (e.g., for pre-COVID: $\bar{t}$ is measured as 18, i.e., 18 months before waves 1 and 2 survey while post-COVID captures the time period for canceled/postponed trips and taken trips during COVD-19). β_2 is the coefficient estimate for travel cost. In addition, price elasticities were calculated using $\beta_2 * \overline{TC}$ (Bowker et al. 2007), where $\overline{TC}$ is the average value of travel cost.

3.7 Data

We combined the data for both day and overnight trips in the analysis, thus providing 3670 observations. Respondents whose origins were outside of the United States or those whose intended destinations were outside of Georgia were dropped from the analysis. After data cleaning, we had 2,886 observations. The data sample included 44 U.S. states (excluding Alaska, Hawaii, Montana, New Mexico, Rhode Island, and Wyoming). Respondents' origins and destinations are shown in Figures 3.3 and 3.4, respectively.

Among the 2,886 observations, 2,662 observations were in Group 1, while 224 observations were in Group 2 (canceled trips only). The variable descriptions are presented in Table 3.2, while Table 3.3 displays the descriptive statistics of the survey data by group category. For Group 1, the average number of actual and canceled/postponed trips pre-COVID was 6.72, while the number was 3.70 post-COVID. The average full travel cost was \$51.47 and \$73.24 for pre-COVID and post-COVID, respectively. The mean monetary travel cost for pre-COVID (post-COVID) trips was \$22 (\$32.72). For the combined pre- and post-COVID trips for Group 1, the average travel party was 2.45, the average age of the respondents was 57 years, 71% of the respondents were female, 22% had children between 0–17 years of age, and 38% took overnight trips.

The *income* variable is categorical from "under \$24,999" to "250,000 or more." We used the midpoint of each interval except for the last category of the top income. We applied a Pareto curve formula developed by Hout (2004) to estimate the value for the top category. The income was normalized using the consumer price index for all urban consumers (CPI-U) for December 2019 to December 2020, which suggests a top value of $212,057 and an average income of $76,924 for Group 1.

The *subjective norms* and *risk perception* variables concern a group of question constructs as specified in Table 3.2. They were calculated into an index through principal component analysis (PCA), the most common method used to reduce data without loss of information (Jolliffe & Cadima, 2016). The mean values for each category are indicated in Table 3.3 for Groups 1 and 2.

For Group 2, the "canceler-only group," the average number of trips canceled was 2.39. The average full travel cost was $133, and the mean value for monetary travel cost was $71. The average travel party size was 2.05, and the average age of respondents was 61 years, while the average income was $60,796; 73% of the respondents were female, 14% had children under the age of 18 in their household, and 45% had canceled overnight trips.

Table 3.2: Variable Description for the Travel Cost Demand Model Analysis

Variables	Description
Trips	Group 1: number of actual and canceled/postponed planned recreational/leisure day and overnight trips Group 2: number of canceled day and overnight trips for potential visitors to Georgia.
Full travel cost	The travel cost, which accounts for both monetary and opportunity cost of time
Monetary travel cost	The monetary component travel cost for driving cost and flying cost, e.g., driving cost is estimated at 0.1787/mile multiplied by round-trip distance divided by average travel party size
Time travel cost	The time component of the travel cost accounts for the opportunity cost of time at destination, driving, and flying time
Travel party	Number of people in the travel party
Overnight trip	Dummy variable for trip type, where 1 denotes overnight and 0 a day trip
Age	Age of the respondents
Income	Respondents' annual household income before taxes
Risk perception (rp)	What is the probability that traveling within the U.S. in the next six months will lead you to? rp1 – Be around others with COVID-19. rp2 – Contract COVID-19. rp3 – Be hospitalized due to COVID-19 1 = not probable, 2 = somewhat probable, 3 = neutral, 4 = somewhat probable, and 5 = probable
Subjective norms (sn)	Please continue to indicate your level of agreement with the following statements. sn1 – Most people who are important to me think I should travel within the U.S. in the near future. sn2 – The people in my life whose opinions I value would approve of me traveling within the U.S. in the near future. sn3 – Most people who are important to me would travel within the U.S. in the near future. 1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, and 5 = strongly agree
Wave dummy	The dummy representing the wave in which the data was collected: Wave 1, June–July 2020; wave 2, October – November 2020; wave 3, August 2021
Female	Dummy for female respondents
With children	Dummy for respondents with children under 18

Table 3.3: Descriptive Statistics of Survey Data by Group

Variable	Group 1: Past visitors and had to cancel intended recreation/leisure trips (*N* = 2662)				Group 2: Potential visitors (canceler only) (N = 224)			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Trips (pre-COVID)	6.72	8.46	1	100	0	0	0	0
Trips (post-COVID)	3.70	4.54	1	60	2.39	2.81	1	20
Full travel cost (pre-COVID) ($)	51.47	80.87	0.65	802.48	0	0	0	0
Full travel cost (post-COVID) ($)	73.24	93.56	0.47	772.92	133.26	126.58	2.1	587.16
Monetary travel cost (pre-COVID) ($)	22.15	36.73	0.28	336.58	0	0	0	0
Monetary travel cost (post-COVID) ($)	32.72	44.16	0.29	405.4	71.12	71.437	.54	389.98
Time travel cost (pre-COVID) ($)	29.32	47.15	0.21	465.9	0	0	0	0
Time travel cost (post-COVID) ($)	40.52	53.86	0.16	503.99	62.14	67.56	1.03	408.19
Travel party	2.45	1.86	1	50	2.045	.927	1	6
Age	57.10	11.56	21	72	61.683	10.653	21	72
Income ($)	76924.41	46730.78	8928.21	212057.14	60795.76	42559	8928.21	212057.14
Female	0.71	0.45	0	1	0.73	0.44	0	1
With children	0.22	0.41	0	1	0.14	0.35	0	1
Post-COVID	0.43	0.50	0	1	1	0	1	1
Overnight trips	0.38	0.49	0	1	0.45	0.50	0	1
rp1	3.41	1.33	1	5	3.33	1.45	1	5
rp2	2.91	1.27	1	5	3.00	1.37	1	5
rp3	2.40	1.20	1	5	2.64	1.32	1	5
sn1	2.60	1.19	1	5	2.17	1.02	1	5
sn2	2.78	1.26	1	5	2.34	1.08	1	5
sn3	2.87	1.23	1	5	2.55	1.08	1	5
Wave dummy	1.60	0.67	1	3	1.71	0.70	1	3

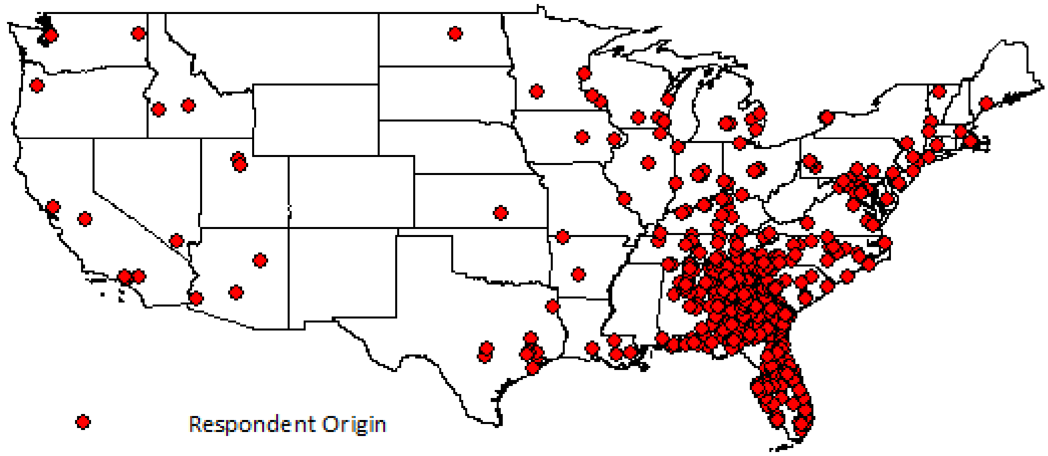

Figure 3.3: Origin of survey respondents within the United States for Georgia tourists.

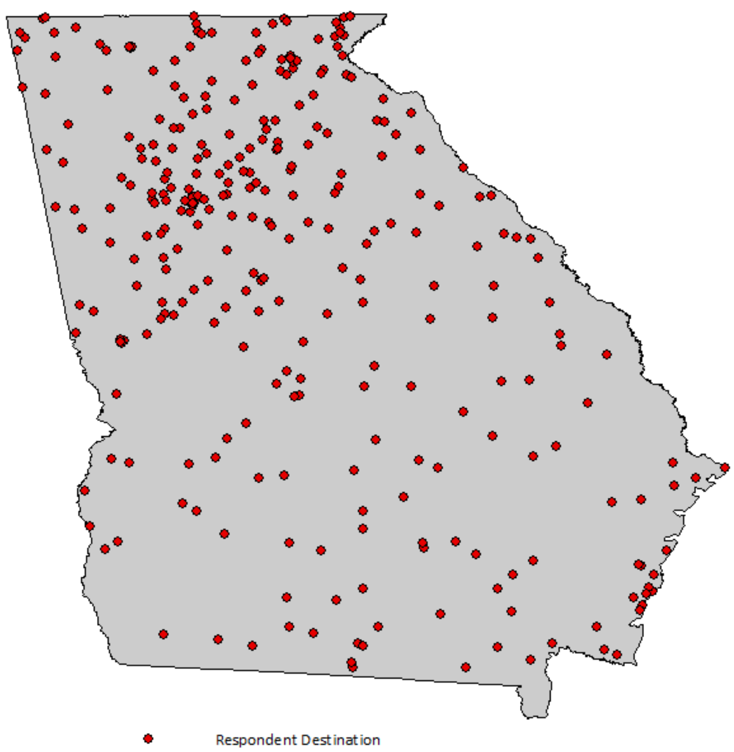

Figure 3.4: Survey respondents' destination town/city within Georgia.

3.8 Results

Tables 3.4a and 3.4b show the travel cost recreation demand model results for actual and canceled/postponed recreation/leisure trips to the state of Georgia for Group 1 (respondents who specified that they had taken recreation/leisure trips to Georgia and canceled planned day and/or overnight trips due to COVID-19). The tables also show the results of hypothesis testing, i.e., the impact of subjective norms on WTP. Specifically, Table 3.4a shows the model estimation results without the consideration of subjective norms (*sn*) in the recreation demand estimates (based on Equation 10a), while Table 3.4b shows the estimates with subjective norms (*sn*) (based on Equation 10b).

The *full travel cost* coefficients in Table 3.4a and 3.4b were statistically significant at 1% across the four models: Poisson, negative binomial, RE-Poisson, and RE-negative binomial. The coefficient was negative and consistent with the theory of demand, which states that as prices increase, the quantity demanded decreases. In this context, as travel cost increased, the number of trips[10] to Georgia decreased. Compared to the values in Table 3.4a, we observed a decrease in the *full travel cost* coefficients in Table 3.4b (model with subjective norms). Price elasticity measures the degree of responsiveness of trips to change in price (travel cost), i.e., the percentage change in trips resulting from the percentage change in price (travel cost).

The price elasticity estimates from the recreation demand model for the negative binomial and RE-Poisson models were both -0.081. The price elasticity estimates for the Poisson and RE-NB models were -0.058 and -0.056, respectively. These elasticity values ranged from -0.056 to -0.081, which is consistent with previous literature (Landry et al., 2021; Phaneuf & Smith, 2005).

[10] Trips interpretation is for the combination of actual and planned trips. Planned trips were canceled due to COVID-19. The results interpretation categorized both actual and planned trips as trips.

When the elasticity value lies between -1 and 0, as in this case, the demand for recreation is inelastic. This result implies that as travel cost increased, the number of leisure trips to Georgia decreased, although the percentage decrease in trips is smaller than the percentage increase in travel cost.

The coefficient estimates for *subjective norms* in Table 3.4b was positive and statistically significant at the 1% level in the RE-negative binomial model, 5% level in the Poisson model, and 10% level in the negative binomial and RE-Poisson models. The subjective norms estimate for the Poisson model was 0.0326 (like the other three models), which implies that as individuals agreed with the opinion of relevant others in their life about recreational travel, the number of trips increased by 0.0326. A full model that includes interaction variables between subjective norms and travel cost is presented in Appendix Table C1. The coefficient for the interaction between subjective norms and travel cost was not statistically significant, which implies that the shift in the recreation demand model due to subjective norms does not change the slope.

Aside from travel cost and subjective norms, we inspected the significance of other explanatory variables in our model. The *risk perception* coefficient for the model with subjective norms (Table 3.4b) was statistically significant at the 10% level for the negative binomial, RE-Poisson, and RE-negative binomial models. In contrast, *risk perception* was not statistically significant in the Poisson model in Table 4b nor across the four models in Table 3.4a (model without subjective norms). The *travel party* coefficient estimate was not statistically significant. The coefficient estimates for the *overnight trip* were negative and statistically significant at the 1% level across the four models. This result implies that Georgia tourists took fewer overnight trips than day trips. Focusing on the socioeconomic variables, the coefficient estimate for *income* was positive and statistically significant at the 1% level for the four models. This result suggests that tourists took more trips to Georgia as income increased. Across all models, females took fewer trips than males; respondents with children under age 18 also took fewer trips. The post-COVID variable was negative and statistically significant at 1%, implying that people took fewer recreational trips post-COVID. The number of recreation/leisure trips taken during wave 2 (i.e., October–November 2020) was greater than in wave 1 (June–July 2020), while by wave 3, August 2021, recreation trips taken totaled more than those taken in waves 1 and 2.

For the welfare estimates or consumer surplus, which is equal to the negative inverse of the travel cost coefficient in Table 3.4a, i.e., the models without subjective norms, the average per person per trip consumer surplus or WTP was $1057.54 with a 95% confidence interval of $455.87 to $1659.21 for the negative binomial and RE-Poisson models. In comparison with the WTP values in Table 3.4b (model with subjective norms), the values were higher, and the average per person per trip consumer surplus (i.e., net economic value or WTP) was estimated at $1044.48 using the negative binomial and RE-Poisson models with a 95% confidence interval of $453.24 to $1635.71.

The *annualized* difference between pre- and post-COVID welfare estimates is presented in the last row of Table 3.4a and 3.4b. These annualized welfare estimates (or WTP or consumer surplus) in absolute values showed a net decrease in consumer surplus related to COVID-19. For Table 4a, the values were $1862.63 (Poisson), $2604.59 (negative binomial and RE-Poisson), and $2722.60 (RE-negative binomial), whereas for Table 4b (model with subjective norms), the values were $1830.88 (Poisson), $2572.42 (negative binomial and RE-Poisson), and $2667.77 (RE-negative binomial).

In Tables 3.4a and 3.4b, the Akaike information criterion (AIC) and the Bayesian information criterion (BIC) were used for model diagnostics to determine optimal model performance. Models with smaller AIC and BIC values are assumed to perform better. As shown in Table 3.4b (model with subjective norms), the AIC values were smaller across the four models compared to Table 3.4a (model without subjective norms). Similarly, the BIC values in Table 3.4b (model with subjective norms) were smaller than those in Table 3.4a for the Poisson model, which reinforces our study's hypothesis. Although the BIC values for Table 3.4b (model with subjective norms) for negative binomial, RE-Poisson, and RE-negative binomial were larger than in Table 3.4a (model without subjective norms), this could be because sometimes BIC tends to be more parsimonious when penalizing model complexity.

In Tables 3.5a and 3.5b, we combined the data for Groups 1 and 2, i.e., actual and potential Georgia visitors. The regression estimates were consistent with the results in Tables 3.4a and 3.4b, except that while *subjective norms* was positive across the four models, this variable was only statistically significant in the Poisson and RE-negative binomial models. Since we combined actual and potential tourists, it may be that the subjective norms variable affected the actual use, but not the possible/potential use, of recreation/leisure commodities. The full travel cost coefficient was negative and statistically significant at 1% among the four models in both Table 3.5a and 3.5b. The WTP estimates for the models with subjective norms (Table 3.5b) were smaller than those without subjective norms (Table 3.5a). The AIC and BIC values for all the models in Table 3.5b (model with subjective norms) were smaller than the values for the models without subjective norms (Table 3.5a).

Table 3.4a: Georgia Recreational Trip Demand Model (Full Travel Cost) Without Subjective Norms

Dependent variable: number of trips (i.e. number of actual and cancel planned trips)

Variables	Poisson	Negative Binomial	Random Effects Poisson	Random Effects Negative Binomial
Full travel cost	-0.00132***	-0.000946***	-0.000946***	-0.000905***
	(0.000300)	(0.000274)	(0.000274)	(0.000180)
Risk perception	0.0221	0.0259	0.0259	0.0232
	(0.0240)	(0.0201)	(0.0201)	(0.0153)
Travel party	-0.000657	0.00669	0.00669	0.00617
	(0.0115)	(0.00944)	(0.00944)	(0.00901)
Overnight trips	-0.668***	-0.630***	-0.630***	-0.569***
	(0.0472)	(0.0435)	(0.0435)	(0.0281)
Income	0.0000017***	0.0000018***	0.0000018***	0.0000016***
	(0.00000059)	(0.00000052)	(0.00000052)	(0.00000041)
Age	-0.00818***	-0.00671***	-0.00671***	-0.00578***
	(0.00254)	(0.00222)	(0.00222)	(0.00164)
Female	-0.169***	-0.143***	-0.143***	-0.120***
	(0.0559)	(0.0493)	(0.0493)	(0.0327)
With children	-0.117*	-0.119**	-0.119**	-0.0997**
	(0.0680)	(0.0595)	(0.0595)	(0.0441)
Post-COVID	-0.752***	-0.723***	-0.723***	-0.593***
	(0.0462)	(0.0442)	(0.0442)	(0.0366)
Wave dummy = 2	0.159***	0.175***	0.175***	0.107***
	(0.0520)	(0.0468)	(0.0468)	(0.0390)
Wave dummy = 3	0.662***	0.638***	0.638***	0.530***
	(0.0775)	(0.0704)	(0.0704)	(0.0569)
Constant	2.571***	2.399***	2.399***	2.711***
	(0.196)	(0.162)	(0.162)	(0.145)
Observations	2,662	2,662	2,662	2,662
Log likelihood	-9905.7192	-6953.82	-6955.97	-6832.07
AIC	19835.44	13937.94	13937.94	13692.14
BIC	19906.08	14014.47	14014.47	13774.56
CS per trip	756.28[419.71, 1092.86]	1057.54[455.87, 1659.21]	1057.54[455.99, 1659.10]	1105.46[575.13, 1635.78]
CS (pre-COVID)	3386.93[1879.61, 4894.24]	4736.08[2041.58, 7430.58]	4736.08[2042.09, 7430.07]	4950.66[2575.66, 7325.66]
CS (post-COVID)	1524.30[845.92, 2202.67]	2131.49[918.82, 3344.15]	2131.49[919.05, 3343.92]	2228.06[1159.19, 3296.93]
CS (diff pre- & post-COVID)	1862.63[1033.69, 2691.57]	2604.59[1122.76, 4086.43]	2604.59[1123.04, 4086.15]	2722.60[1416.48, 4028.726]

Notes: *** p<0.01, ** p<0.05, * p<0.1, robust standard errors in parentheses. Confidence interval estimates at 95% computed using the delta method are in brackets.

Table 3.4b: Georgia Recreational Trip Demand Model Estimates (Full Travel Cost) With Subjective Norms

Dependent variable: number of trips (i.e., number of actual and cancel planned trips)

Variables	Poisson	Negative Binomial	Random Effects Poisson	Random Effects Negative Binomial
Full travel cost	-0.00135***	-0.000957***	-0.000957***	-0.000923***
	(0.000300)	(0.000277)	(0.000276)	(0.000188)
Risk perception	0.0346	0.0339*	0.0339*	0.0332*
	(0.0247)	(0.0205)	(0.0205)	(0.0189)
Subjective norms	**0.0326****	**0.0224***	**0.0224***	**0.0270*****
	(0.0137)	**(0.0126)**	**(0.0126)**	**(0.0102)**
Travel party	-0.00183	0.00561	0.00561	0.00517
	(0.0115)	(0.00941)	(0.00941)	(0.00946)
Overnight trips	-0.672***	-0.633***	-0.633***	-0.572***
	(0.0472)	(0.0435)	(0.0435)	(0.0350)
Income	0.0000017***	0.0000018***	0.0000018***	0.0000016***
	(0.00000059)	(0.00000052)	(0.00000052)	(0.00000037)
Age	-0.00733***	-0.00610***	-0.00610***	-0.00509***
	(0.00253)	(0.00220)	(0.00220)	(0.00153)
Female	-0.164***	-0.139***	-0.139***	-0.115***
	(0.0557)	(0.0492)	(0.0492)	(0.0350)
With children	-0.110	-0.111*	-0.111*	-0.0934**
	(0.0677)	(0.0593)	(0.0592)	(0.0457)
Post-COVID	-0.744***	-0.715***	-0.715***	-0.586***
	(0.0461)	(0.0444)	(0.0444)	(0.0270)
Wave dummy = 2	0.139***	0.159***	0.159***	0.0916**
	(0.0519)	(0.0471)	(0.0471)	(0.0373)
Wave dummy = 3	0.629***	0.616***	0.616***	0.503***
	(0.0797)	(0.0724)	(0.0724)	(0.0560)
Constant	2.529***	2.369***	2.369***	2.674***
	(0.195)	(0.160)	(0.160)	(0.129)
Observations	2,662	2,662	2,662	2,662
Log likelihood	-9887.1922	-6953.82	-6953.82	-6828.93
AIC	19800.38	13935.64	13935.64	13687.87
BIC	19876.91	14018.05	14018.05	13776.17
CS per trip	743.39[418.03, 1068.75]	1044.48[453.24, 1635.71]	1044.48[453.35, 1635.60]	1083.19[573.98, 1592.41]
CS (pre-COVID)	3329.20[1872.12, 4786.28]	4677.57[2029.80, 7325.34]	4677.57[2030.30, 7324.844]	4850.95[2570.50, 7131.41]
CS (post-COVID)	1498.32[842.55, 2154.08]	2105.15[913.52, 3296.79]	2105.15[913.74, 3296.57]	2183.19[1156.86, 3209.51]
CS (diff pre- & post-COVID)	1830.88[1029.57, 2632.20]	2572.42[1116.28, 4028.55]	2572.42[1116.56, 4028.28]	2667.77[1413.64, 3921.90]

Notes: *** p<0.01, ** p<0.05, * p<0.1, robust standard errors in parentheses. Confidence interval estimates at 95% computed using the delta method are in brackets..

Table 3.5a: Georgia Recreational Trip Demand Model trips (Full Travel Cost), Including Canceller-Only (Groups 1 and 2 Combined) Without Subjective Norms

Dependent variable: number of trips (i.e., number of trips for actual, planned cancel, and canceler only group)

Variables	Poisson	Negative Binomial	Random Effects Poisson	Random Effects Negative Binomial
Full travel cost	-0.00135***	-0.000993***	-0.000993***	-0.000963***
	(0.000275)	(0.000250)	(0.000249)	(0.000166)
Risk perception	0.0176	0.0216	0.0216	0.0199
	(0.0222)	(0.0187)	(0.0187)	(0.0151)
Travel party	-0.00245	0.00556	0.00556	0.00506
	(0.0120)	(0.00937)	(0.00937)	(0.00855)
Overnight trips	-0.659***	-0.618***	-0.618***	-0.556***
	(0.0455)	(0.0418)	(0.0418)	(0.0309)
Income	0.000002***	0.000002***	0.000002***	0.000002**
	(0.0000006)	(0.0000005)	(0.0000005)	(0.0000004)
Age	-0.00842***	-0.00699***	-0.00699***	-0.00608***
	(0.00244)	(0.00212)	(0.00212)	(0.00157)
Female	-0.172***	-0.147***	-0.147***	-0.124***
	(0.0543)	(0.0477)	(0.0477)	(0.0330)
With children	-0.103	-0.103*	-0.103*	-0.0862**
	(0.0663)	(0.0573)	(0.0573)	(0.0439)
Post-COVID	-0.770***	-0.743***	-0.743***	-0.619***
	(0.0445)	(0.0428)	(0.0428)	(0.0308)
Wave dummy = 2	0.146***	0.156***	0.156***	0.0969***
	(0.0505)	(0.0450)	(0.0450)	(0.0305)
Wave dummy = 3	0.643***	0.612***	0.612***	0.511***
	(0.0744)	(0.0677)	(0.0676)	(0.0527)
Constant	2.593***	2.425***	2.425***	2.791***
	(0.189)	(0.155)	(0.155)	(0.144)
Observations	2,886	2,886	2,886	2,886
Log likelihood	-10408.99	-7400.66	-7400.66	-7271.43
AIC	20841.97	14827.32	14827.32	14570.86
BIC	20913.58	14904.9	14904.9	14654.41
CS per trip	742.04[444.72, 1039.35]	1006.76[511.09, 1502.43]	1006.76[511.18, 1502.34]	1038.71[643.63, 1433.79]
CS (pre-COVID)	3323.12[1991.65, 4654.60]	4508.65[2288.85, 6728.45]	4508.65[2289.24, 6728.06]	4651.72[2882.41, 6421.04]
CS (post-COVID)	1408.92[844.41, 1973.43]	1911.55[970.41, 2852.68]	1911.55[970.58, 2852.52]	1972.21[1222.07, 2722.35]
CS (diff pre- & post-COVID)	1914.21[1147.24, 2681.17]	2597.10[1318.44, 3875.76]	2597.10[1318.66, 3875.54]	2679.52[1660.34, 3698.69]

Notes: *** p<0.01, ** p<0.05, * p<0.1, robust standard errors in parentheses. Confidence interval estimates at 95% computed using the delta method are in brackets..

Table 3.5b: Georgia Recreational Trip Demand Model (Full Travel Cost), Including Canceller-Only (Groups 1 and 2 Combined) With Subjective Norms

Dependent variable: number of trips (i.e., number of trips for actual, planned cancel, and canceler only group)

Variables	Poisson	Negative Binomial	Random Effects Poisson	Random Effects Negative Binomial
Full travel cost	-0.00136***	-0.000999***	-0.000999***	-0.000972***
	(0.000275)	(0.000250)	(0.000250)	(0.000165)
Risk perception	0.0272	0.0274	0.0274	0.0274*
	(0.0227)	(0.0191)	(0.0191)	(0.0147)
Subjective norms	**0.0296****	**0.0190**	**0.0190**	**0.0236****
	(0.0134)	**(0.0122)**	**(0.0122)**	**(0.0105)**
Travel party	-0.00354	0.00453	0.00453	0.00415
	(0.0119)	(0.00933)	(0.00933)	(0.0101)
Overnight trips	-0.662***	-0.620***	-0.620***	-0.558***
	(0.0455)	(0.0418)	(0.0418)	(0.0288)
Income	0.000002***	0.000002***	0.000002***	0.000002***
	(0.0000006)	(0.0000005)	(0.0000005)	(0.0000004)
Age	-0.00765***	-0.00647***	-0.00647***	-0.00547***
	(0.00243)	(0.00210)	(0.00210)	(0.00173)
Female	-0.167***	-0.143***	-0.143***	-0.120***
	(0.0542)	(0.0477)	(0.0477)	(0.0343)
With children	-0.0953	-0.0955*	-0.0955*	-0.0800**
	(0.0660)	(0.0571)	(0.0571)	(0.0407)
Post-COVID	-0.762***	-0.735***	-0.735***	-0.613***
	(0.0443)	(0.0430)	(0.0430)	(0.0318)
Wave dummy = 2	0.128**	0.143***	0.143***	0.0836**
	(0.0504)	(0.0453)	(0.0453)	(0.0365)
Wave dummy = 3	0.614***	0.594***	0.594***	0.489***
	(0.0762)	(0.0693)	(0.0693)	(0.0675)
Constant	2.554***	2.399***	2.399***	2.757***
	(0.188)	(0.154)	(0.154)	(0.136)
Observations	2,886	2,886	2,886	2,886
Log likelihood	-10393.20	-7399.01	-7399.01	-7268.87
AIC	20812.4	14826.01	14826.01	14567.74
BIC	20889.98	14909.56	14909.56	14657.25
CS per trip	734.82[443.55, 1026.08]	1001.34[509.16, 1493.52]	1001.34[509.24, 1493.43]	1029.11[614.94, 1443.28]
CS (pre-COVID)	3290.79[1986.40, 4595.18]	4484.37[2280.20, 6688.54]	4484.37[2280.58, 6688.16]	4608.77[2753.96, 6463.57]
CS (post-COVID)	1395.21[842.18, 1948.23]	1901.25[966.74, 2835.76]	1901.25[966.90, 2835.60]	1954.00[1167.61, 2740.38]
CS (diff pre- & post-COVID)	1895.58[1144.22, 2646.94]	2583.11[1313.45, 3852.78]	2583.11[1313.67, 3852.55]	2654.77[1586.35, 3723.19]

Notes: *** p<0.01, ** p<0.05, * p<0.1, robust standard errors in parentheses. Confidence interval estimates at 95% computed using the delta method are in brackets..

3.9 Sensitivity Analysis

To check for robustness in our estimation results, we first used out-of-pocket travel cost instead of the full travel cost that included time cost (Landry et al., 2021; Lupi et al., 2020). Our regression results in Appendix B, Tables D1 and D2, are for the monetary travel cost model. For the negative binomial and RE-Poisson models, the average per person per trip consumer surplus was $422.12 with a 95% confidence interval of $192.77 to $651.43. However, these values are smaller than the full travel cost model because they account only for the out-of-pocket components of the travel cost.

Second, the value of time used in the recreation demand model has been debated. Some authors have suggested using one-third of the average wage rates (Cesario, 1976; Fezzi et al., 2014), while others have recommended using one-half of the average wage rates (Rogoff, 2014; Wolff, 2014). Therefore, we checked the strength of our estimates by using one-half of the average wage rates for the opportunity cost of time. The regression results presented in Tables D3 and D4 showed a higher average consumer surplus per person for negative binomial and RE-Poisson at $1380.22, with a 95% confidence interval of $581.44 to $2,131.83. These results were consistent with the estimates in previous sections, confirming the robustness of our estimation results. However, the net economic values were higher than the earlier estimates using one-third of the average wage rate (Fezzi et al., 2014).

Third, we assumed estimates of travel costs to be all driving costs (Alvarez et al., 2014; English et al., 2018; Glasgow & Train, 2018), with the results presented in Tables D5 and D6. The results were consistent with the previous estimate; the differences in the net economic values were relatively small. The hypothesis testing of the effects of subjective norms on the demand for and net economic value of recreation/leisure trips remained consistent with the original estimation shown in Tables 3.4a and 3.4b.

3.10 Discussion and Conclusions

The study's primary purpose was to model conceptually and test empirically for the effects of subjective norms on the demand for and value of recreational/leisure trips to the state of Georgia. Specific objectives included estimating the economic loss expressed in consumer surplus (or WTP) experienced by tourists who had planned to visit Georgia but canceled/postponed their recreation/leisure trip due to the COVID-19 pandemic. Our results showed that the subjective norms variable was statistically significant across all models and had a positive effect on the demand for recreational/leisure travel, and this result was consistent with our expectation. The result is consistent with Bae and Chang (2020), who found that subjective norms positively influenced behavioral intention toward “untact” (no-contact) tourism.

Furthermore, the coefficient of *full travel cost*, one essential explanatory variable in travel cost recreation demand, supported the study hypothesis. The *full travel cost* coefficient in our model estimation was lower in the model with subjective norms compared to the model without. This result indicated that WTP decreased with the inclusion of the subjective norms variable in model estimation since WTP was measured as the negative inverse of travel cost. The estimate of WTP in our model also confirmed the above, and the annualized consumer surplus or WTP pre- and post-COVID for models with subjective norms was smaller. Similarly, the AIC and BIC criteria for model selection showed that the model with subjective norms performed better. This result further validated the study hypothesis that subjective norms reduce WTP due to COVID-19, i.e., subjective norms encourage an individual to cancel/postpone leisure/recreation trips due to COVID-19. This study result is also consistent with previous studies that have found sociopsychological factors such as subjective norms to influence individual WTP (Ajzen & Driver, 1992; Bernath & Roschewtiz, 2008; Meleddu & Pulina, 2016). In contrast, López-Mosquera (2016) and Spash et al. (2009) could not confirm the effect of subjective norms on WTP.

Previous literature on psychological factors constructs from TPB on WTP for environmental goods has focused largely on stated preference (i.e., contingent valuation). These studies have also generally used all three variables in TPB—attitudes, perceived behavioral control, subjective norms—and ignored other explanatory variables considered in nonmarket valuation literature. This study contributes to the environmental commodities valuation literature in two ways: 1) by developing a conceptual model and empirically testing the impact of subjective norms on WTP using a revealed preference approach and 2) by accounting for other explanatory variables such as travel cost, risk perception, and socioeconomic factors in addition to subjective norms. Finally, we also contribute to the growing literature that estimates the costs of COVID-19, by estimating the economic loss from reduced travel, but from the perspective of the welfare of individual travelers.

Understanding the factors that influence WTP for recreation commodities in Georgia—can help the government and the tourism industry improve marketing strategy efficiency and increase visitor satisfaction levels.

This study's WTP values per trip were much larger than previous recreation demand literature focusing on a single site. Although our research concentrated on several leisure sites within Georgia, it accounted for indoor and outdoor as well as day and overnight trips. The consumer surplus found in this paper cannot be used in benefit transfer studies because we focused on multiple sites and not on a single site and different recreation activities. Landry et al. (2021), in their study on outdoor recreation across several sites within the U.S., also found a substantial estimate for consumer surplus. Consistent with our hypothesis, we found WTP (or consumer surplus) to be higher for models without subjective norms, thereby providing evidence that subjective norms are an important recreation demand shifter and should be considered in future research. For future studies, we encourage both the conceptual and empirical testing of the effects of subjective norms on specific recreation activity demands in single and multiple site settings, such as boating, and fishing recreation demands

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Chapter 3 Appendices: Appendix B, Flying Cost Estimation

$$TC_{ij}^{F} = TC_{ij}^{D}(origin, airport) + C_{parking} + C_{flight} + C_{carrental} + TC_{ij}^{D}(airport, city)$$

TC_{ij}^{F} is the cost of flying from respondents' origin to city/town within Georgia. We identified four potential airports with the shortest driving distance from the respondent's home to the origin airport and four airports with the shortest driving distance at the destination closest to the city/town within Georgia. We considered only airports with 100,000 enplanements. The airport lists were obtained from the U.S. Department of Transportation, while the Federal Aviation Administration provided enplanement data. We used 155 origin airports and 18 destination airports in our estimation. The flying cost within the origin-destination airport pair with minimum flying cost was kept for the calculation.

$C_{parking}$ is the cost of parking at the origin airport. This was computed as the average cost of parking at the airport multiplied by the number of parking days assumed to be the average number of intended nights spent on a trip divided by the average travel party size. The cost of parking at the airport for different airports was obtained from English et al. (2018), and these values were adjusted for inflation to reflect 2020 rates using the consumer price index for all urban consumers.

$$C_{flight} = p_{ticket} + \alpha_i \left(time_{airport} + time_{flight} + time_{layover}\right)$$

Where:

p_{ticket} is the ticket price of the flight from origin airports to destination airports. The itinerary fare per person was obtained from airline origin-destination survey data from Bureau of Transportation statistics. We used the data for quarters 1, 2, 3, and 4 in 2019 and then calculated the average itinerary fare for 2019, which we used in our analysis. Baggage fees of $50 were added except for JetBlue and Southwest Airlines.

α_i is the opportunity cost of time, which is the standard 33% of the wage rates. The $time_{flight}$ is the time spent in flight from the origin airport to the destination airport; this was obtained by dividing the flight distance by the airspeed. The flight distance was provided in airline origin-destination survey data from Bureau of Transportation statistics. The airspeed for a commercial airline is between 547–575 mph and was provided by Epic Flight Academy; we assumed the average figure (560 mph) for the airspeed. The time layover was assumed to be 60 minutes, which is usually the recommended time for domestic flights in the United States.

$C_{carrental}$ is the cost of renting a car for the respondents who chose to fly, calculated as the average daily cost of a rental car multiplied by the average number of intended nights multiplied by the average proportion of respondents renting cars on flying trips divided by the average travel party. The average daily cost of rental cars from January to June 2021 was obtained from Hooper.

Chapter 3 Appendices: Appendix C, Full Models

Table C1: Georgia Recreation Trip Demand: Full Travel Cost Model with Subjective Norms (Full Models with interaction variables)

Dependent variable is number of trips Variables	Poisson	Negative Binomial	Random Effects Poisson	Random Effects Negative Binomial
Full travel cost	-0.00136***	-0.000968***	-0.000968***	-0.000921***
	(0.000305)	(0.000273)	(0.000273)	(0.000219)
Risk Perception	0.00422	0.00234	0.00234	0.00744
	(0.0183)	(0.0154)	(0.0154)	(0.0121)
Subjective Norms	0.0529**	0.0464**	0.0464**	0.0494***
	(0.0224)	(0.0205)	(0.0205)	(0.0172)
Subjective Norms * Post-COVID	-0.0901**	-0.0730**	-0.0730**	-0.0687***
	(0.0351)	(0.0311)	(0.0311)	(0.0261)
Subjective Norms * Full travel cost	0.000043	0.0000374	0.000037	0.0000524
	(0.000225)	(0.000193)	(0.000192)	(0.000183)
Subjective Norms * Full travel cost * Post-COVID	0.000078	-0.000054	-0.000054	-0.000048
	(0.000399)	(0.000328)	(0.000328)	(0.000260)
travel party	-0.00201	0.00608	0.00608	0.00524
	(0.0116)	(0.00924)	(0.00923)	(0.00986)
Overnight trips	-0.672***	-0.632***	-0.632***	-0.573***
	(0.0471)	(0.0437)	(0.0436)	(0.0322)
Income	0.0000017***	0.0000018***	0.0000076***	0.0000016***
	(0.00000059)	(0.00000052)	(0.00000052)	(0.00000038)
Age	-0.00736***	-0.00604***	-0.00604***	-0.00512***
	(0.00254)	(0.00218)	(0.00218)	(0.00163)
Female	-0.167***	-0.142***	-0.142***	-0.118***
	(0.0559)	(0.0493)	(0.0492)	(0.0339)
With Children	-0.111	-0.111*	-0.111*	-0.0937*
	(0.0677)	(0.0590)	(0.0590)	(0.0489)
Post-COVID	-0.748***	-0.718***	-0.718***	-0.591***
	(0.0467)	(0.0448)	(0.0447)	(0.0336)
wave dummy = 2	0.136***	0.154***	0.154***	0.0890**
	(0.0518)	(0.0471)	(0.0471)	(0.0386)
wave dummy = 3	0.676***	0.646***	0.646***	0.538***
	(0.0814)	(0.0729)	(0.0729)	(0.0646)
Constant	2.531***	2.366***	2.366***	2.684***
	(0.194)	(0.158)	(0.158)	(0.148)
Observations	2,662	2,662	2,662	2,662
Log Likelihood	-9863.39	-6948.895	-6953.82	-6824.61
AIC	19758.78	13931.79	13931.79	13685.23
BIC	19852.97	14031.87	14031.87	13791.19
CS per trip	736.06[411.76 1060.37]	1033.34[461.81 1604.87]	1033.34[461.92 1604.77]	1085.584[559.32 1592.41]

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Confidence interval estimates at 95% computed using the delta method are in brackets

Chapter 3 Appendices: Appendix D, Sensitivity Analysis Tables

Table D1: Georgia Recreational Trip Demand (Monetary Travel Cost) Without Subjective Norms

Dependent variable: number of trips (i.e., number of actual and cancel planned trips)				
Variables	Poisson	Negative Binomial	Random Effects Poisson	Random Effects Negative Binomial
Monetary travel cost	-0.00336***	-0.00233***	-0.00233***	-0.00226***
	(0.000660)	(0.000648)	(0.000647)	(0.000372)
Risk perception	0.0231	0.0260	0.0260	0.0239*
	(0.0240)	(0.0201)	(0.0201)	(0.0138)
Travel party	-0.000800	0.00638	0.00638	0.00607
	(0.0116)	(0.00943)	(0.00943)	(0.00944)
Overnight trips	-0.665***	-0.626***	-0.626***	-0.566***
	(0.0471)	(0.0435)	(0.0434)	(0.0331)
Income	1.26e-06**	0.000001***	0.000001***	0.000001***
	(5.70e-07)	(0.0000005)	(0.0000005)	(0.00000036)
Age	-0.00807***	-0.00661***	-0.00661***	-0.00570***
	(0.00254)	(0.00222)	(0.00222)	(0.00163)
Female	-0.172***	-0.144***	-0.144***	-0.121***
	(0.0558)	(0.0493)	(0.0493)	(0.0355)
With children	-0.118*	-0.120**	-0.120**	-0.100**
	(0.0680)	(0.0595)	(0.0595)	(0.0457)
Post-COVID	-0.748***	-0.718***	-0.718***	-0.589***
	(0.0462)	(0.0441)	(0.0441)	(0.0318)
Wave dummy = 2	0.157***	0.174***	0.174***	0.105***
	(0.0520)	(0.0467)	(0.0467)	(0.0361)
Wave dummy = 3	0.657***	0.631***	0.631***	0.525***
	(0.0744)	(0.0703)	(0.0702)	(0.0531)
Constant	2.606***	2.423***	2.423***	2.741***
	(0.196)	(0.162)	(0.162)	(0.143)
Observations	2,662	2,662	2,662	2,662
Log likelihood	-9888.52	-6953.01	-6953.01	-6829.17
AIC	19801.04	13932.03	13932.03	13686.33
BIC	19871.69	14008.56	14008.56	13768.75
CS per trip	297.50[182.97 412.04]	428.31[195.49, 661.14]	428.31[195.53, 661.10]	443.34[260.01, 626.67]
CS (pre-COVID)	1332.34[819.40 1845.28]	1918.16[875.48, 2960.84]	1918.16[875.67, 2960.64]	1985.45[1164.41, 2806.48]
CS (post-COVID)	599.62[368.77 830.47]	863.27[394.01, 1332.53]	863.27[394.10, 1332.45]	893.56[524.05, 1263.07]
CS (diff pre- & post-COVID)	732.72[450.63 1014.81]	1054.89[481.47, 1628.31]	1054.89[481.57, 1628.20]	1091.89[640.36, 1543.42]

Notes: *** p<0.01, ** p<0.05, * p<0.1, robust standard errors in parentheses. Confidence interval estimates at 95% computed using the delta method are in brackets.

Table D2: Georgia Recreational Trip Demand (Monetary Travel Cost) With Subjective Norms

Dependent variable: number of trips (i.e., number of actual and cancel planned trips)

Variables	Poisson	Negative Binomial	Random Effects Poisson	Random Effects Negative Binomial
Monetary travel cost	-0.00343***	-0.00237***	-0.00237***	-0.00231***
	(0.000662)	(0.000657)	(0.000657)	(0.000410)
Risk perception	0.0361	0.0343*	0.0343*	0.0343**
	(0.0247)	(0.0206)	(0.0206)	(0.0173)
Subjective norms	0.0337**	0.0230*	0.0230*	0.0280***
	(0.0137)	(0.0126)	(0.0126)	(0.0108)
Travel party	-0.00201	0.00528	0.00528	0.00502
	(0.0116)	(0.00939)	(0.00939)	(0.00850)
Overnight trips	-0.668***	-0.628***	-0.628***	-0.569***
	(0.0471)	(0.0435)	(0.0435)	(0.0344)
Income	0.000001**	0.000001***	0.000001***	0.000001***
	(0.00000057)	(0.00000005)	(0.0000005)	(0.00000036)
Age	-0.0072***	-0.00597***	-0.00597***	-0.00498***
	(0.00253)	(0.00220)	(0.00220)	(0.00154)
Female	-0.166***	-0.141***	-0.141***	-0.117***
	(0.0556)	(0.0492)	(0.0492)	(0.0383)
With children	-0.110	-0.112*	-0.112*	-0.0941**
	(0.0676)	(0.0592)	(0.0592)	(0.0404)
Post-COVID	-0.740***	-0.710***	-0.710***	-0.583***
	(0.0461)	(0.0443)	(0.0443)	(0.0327)
Wave dummy = 2	0.137***	0.157***	0.157***	0.0897***
	(0.0519)	(0.0470)	(0.0470)	(0.0348)
Wave dummy = 3	0.623***	0.608***	0.608***	0.497***
	(0.0795)	(0.0723)	(0.0723)	(0.0577)
Constant	2.563***	2.392***	2.392***	2.703***
	(0.194)	(0.160)	(0.160)	(0.135)
Observations	2,662	2,662	2,662	2,662
Log likelihood	-9868.76	-6950.75	-6950.75	-6825.80
AIC	19763.52	13929.50	13929.5	13681.61
BIC	19840.05	14011.91	14011.91	13769.91
CS per trip	291.12[181.16, 401.09]	422.12[192.77, 651.47]	422.12[192.81 651.43]	432.31[255.75, 608.87]
CS (pre-COVID)	1303.77[811.30, 1796.23]	1890.41[863.29, 2917.54]	1890.41[863.481, 2917.35]	1936.03[1145.33, 2726.74]
CS (post-COVID)	586.76[365.13, 808.40]	850.79[388.53, 1313.05]	850.79[388.61, 1312.96]	871.32[515.46, 1227.18]
CS (diff pre & post COVID)	717.00[446.17, 987.83]	1039.63[474.76, 1604.49]	1039.63[474.87, 1604.39]	1064.72[629.87, 1499.56]

Notes: *** p<0.01, ** p<0.05, * p<0.1, robust standard errors in parentheses. Confidence interval estimates at 95% computed using the delta method are in brackets.

Table D3: Georgia Recreational Trip Demand Model (Full Travel Cost: Opportunity Cost of Time 50% of Wage Rate) Without Subjective Norms

Dependent variable: number of trips (i.e., number of actual and cancel planned trips)				
Variables	Poisson	Negative Binomial	Random Effects Poisson	Random Effects Negative Binomial
Full travel cost	-0.000998***	-0.000716***	-0.000716***	-0.000684***
	(0.000235)	(0.000213)	(0.000213)	(0.000147)
Risk perception	0.0219	0.0259	0.0259	0.0230
	(0.0240)	(0.0201)	(0.0201)	(0.0143)
Travel party	-0.000649	0.00672	0.00672	0.00618
	(0.0115)	(0.00945)	(0.00944)	(0.00960)
Overnight trips	-0.669***	-0.631***	-0.631***	-0.570***
	(0.0472)	(0.0435)	(0.0435)	(0.0291)
Income	0.000002***	0.000002***	0.000002***	0.000002***
	(0.0000006)	(0.0000005)	(0.0000005)	(0.0000004)
Age	-0.00820***	-0.00673***	-0.00673***	-0.00580***
	(0.00254)	(0.00222)	(0.00222)	(0.00168)
Female	-0.169***	-0.142***	-0.142***	-0.119***
	(0.0559)	(0.0493)	(0.0493)	(0.0360)
With children	-0.117*	-0.119**	-0.119**	-0.0993**
	(0.0681)	(0.0595)	(0.0595)	(0.0429)
Post-COVID	-0.753***	-0.724***	-0.724***	-0.593***
	(0.0462)	(0.0442)	(0.0442)	(0.0297)
Wave dummy = 2	0.159***	0.175***	0.175***	0.107***
	(0.0520)	(0.0468)	(0.0468)	(0.0343)
Wave dummy = 3	0.663***	0.639***	0.639***	0.531***
	(0.0776)	(0.0704)	(0.0704)	(0.0537)
Constant	2.566***	2.395***	2.395***	2.706***
	(0.196)	(0.162)	(0.162)	(0.135)
Observations	2,662	2,662	2,662	2,662
Log likelihood	-9909.32	-6956.60	-6956.60	-6832.68
AIC	19842.63	13939.21	13939.21	13693.35
BIC	19913.27	14015.74	14015.74	13775.77
CS per trip	1001.80[539.37 1464.23]	1397.00[583.49 2210.51]	1397.00[583.65 1659.10]	1461.60[735.58 2187.62]
CS (pre-COVID)	4486.44[2415.50 6557.39]	6256.32[2613.11 9899.52]	6256.32[2613.11 9899.52]	6545.60[3294.20 9797.01]
CS (post-COVID)	2019.14[1087.10 2951.17]	2815.67[1176.04 4455.31]	2815.67[1176.04 4455.31]	2945.87[1482.57 4409.17]
CS (diff pre- & post-COVID)	2467.31[1328.40 3606.22]	3440.64[1437.07 5444.22]	3440.64[1437.45 5443.84]	3599.74[1811.64 5387.84]

Notes: *** p<0.01, ** p<0.05, * p<0.1, robust standard errors in parentheses. Confidence interval estimates at 95% computed using the delta method are in brackets

Table D4: Georgia Recreation Trip Demand Model (Full Travel Cost: Opportunity Cost of Time 50% of Wage Rate) With Subjective Norms

Dependent variable: number of trips (i.e., number of actual and cancel planned trips) Variables	Poisson	Negative Binomial	Random Effects Poisson	Random Effects Negative Binomial
Full travel cost	-0.00101***	-0.000725***	-0.000725***	-0.000698***
	(0.000235)	(0.000214)	(0.000214)	(0.000173)
Risk perception	0.0343	0.0339*	0.0339*	0.0330**
	(0.0247)	(0.0205)	(0.0205)	(0.0162)
Subjective norms	0.0324**	0.0223*	0.0223*	0.0269**
	(0.0137)	(0.0125)	(0.0125)	(0.0117)
Travel party	-0.00182	0.00565	0.00565	0.00518
	(0.0115)	(0.00941)	(0.00941)	(0.00825)
Overnight trips	-0.673***	-0.634***	-0.634***	-0.573***
	(0.0472)	(0.0435)	(0.0435)	(0.0333)
Income	0.000002***	0.000002***	0.000002***	0.000002***
	(0.0000006)	(0.0000005)	(0.0000005)	(0.0000004)
Age	-0.00736***	-0.00612***	-0.00612***	-0.00511***
	(0.00253)	(0.00220)	(0.00220)	(0.00171)
Female	-0.163***	-0.139***	-0.139***	-0.115***
	(0.0557)	(0.0492)	(0.0492)	(0.0318)
With children	-0.110	-0.111*	-0.111*	-0.0931*
	(0.0677)	(0.0592)	(0.0592)	(0.0492)
Post-COVID	-0.746***	-0.716***	-0.716***	-0.587***
	(0.0461)	(0.0444)	(0.0444)	(0.0361)
Wave dummy = 2	0.140***	0.160***	0.160***	0.0920**
	(0.0519)	(0.0471)	(0.0471)	(0.0399)
Wave dummy = 3	0.631***	0.617***	0.617***	0.504***
	(0.0797)	(0.0724)	(0.0724)	(0.0565)
Constant	2.524***	2.365***	2.365***	2.669***
	(0.195)	(0.160)	(0.160)	(0.134)
Observations	2,662	2,662	2,662	2,662
Log likelihood	-9891.00	-6954.47	-6954.47	-6829.58
AIC	19808	13936.95	13936.95	13689.16
BIC	19884.53	14019.36	14019.36	13777.46
CS per trip	985.62[537.98 1433.25]	1380.22[581.29 2179.15]	1380.22[581.44 2179.00]	1433.51[735.19 2131.83]
CS (pre-COVID)	4413.97[2409.30 6418.64]	6181.15[2603.23 9759.07]	6181.15[2603.91 9758.40]	6419.83[3292.48 9547.17]
CS (post-COVID)	1986.52[1084.31 2888.73]	2781.84[1171.59 4392.10]	2781.84[1171.90 4391.79]	2889.26[1481.79 4296.73]
CS (diff pre- & post-COVID)	2427.45[1324.99 3529.91]	3399.31[1431.64 5366.97]	3399.31[1432.01 5366.60]	3530.57[1810.69 5250.44]

Notes: *** p<0.01, ** p<0.05, * p<0.1, robust standard errors in parentheses. Confidence interval estimates at 95% computed using the delta method are in brackets.

Table D5: Georgia Recreation Trip Demand Model (Full Travel Cost: Assumed Driving Travel Cost) Without Subjective Norms

Dependent variable: number of trips (i.e., number of actual and cancel planned trips)

Variables	Poisson	Negative Binomial	Random Effects Poisson	Random Effects Negative Binomial
Full travel cost	-0.00132***	-0.000942***	-0.000942***	-0.000888***
	(0.000306)	(0.000274)	(0.000274)	(0.000180)
Risk perception	0.0221	0.0260	0.0260	0.0230
	(0.0240)	(0.0201)	(0.0201)	(0.0151)
Travel party	-0.000574	0.00672	0.00672	0.00622
	(0.0115)	(0.00944)	(0.00944)	(0.00879)
Overnight trips	-0.669***	-0.631***	-0.631***	-0.570***
	(0.0472)	(0.0434)	(0.0434)	(0.0317)
Income	0.000002***	0.000002***	0.000002***	0.000002***
	(0.0000006)	(0.0000005)	(0.0000005)	(0.0000004)
Age	-0.00820***	-0.00674***	-0.00674***	-0.00582***
	(0.00254)	(0.00222)	(0.00222)	(0.00183)
Female	-0.169***	-0.143***	-0.143***	-0.119***
	(0.0559)	(0.0493)	(0.0493)	(0.0337)
With children	-0.116*	-0.118**	-0.118**	-0.0989**
	(0.0680)	(0.0595)	(0.0595)	(0.0478)
Post-COVID	-0.753***	-0.724***	-0.724***	-0.594***
	(0.0462)	(0.0442)	(0.0442)	(0.0303)
Wave dummy = 2	0.158***	0.174***	0.174***	0.106***
	(0.0520)	(0.0468)	(0.0468)	(0.0352)
Wave dummy = 3	0.663***	0.639***	0.639***	0.531***
	(0.0775)	(0.0704)	(0.0704)	(0.0565)
Constant	2.572***	2.401***	2.401***	2.714***
	(0.196)	(0.162)	(0.162)	(0.151)
Observations	2,662	2,662	2,662	2,662
Log likelihood	-9907.83	-6956.15	-6956.15	-6832.38
AIC	19839.65	13938.29	13938.29	13692.77
BIC	19910.29	14014.82	14014.82	13775.18
CS per trip	756.46[413.35 1099.58]	1061.45[456.94 1665.96]	1061.45[457.05 1665.85]	1125.76[573.34 1678.19]
CS (pre-COVID)	3387.73[1851.141 4924.33]	4753.58[2046.35 7460.82]	4753.58[2046.86 7460.31]	5041.59[2567.62 7515.56]
CS (post-COVID)	1524.66[833.11 2216.21]	2139.36[920.97 3357.76]	2139.36[921.19 3357.53]	2268.98[1155.56 3382.40]
CS (diff pre- & post-COVID)	1863.08[1018.03 2708.12]	2614.22[1125.39 4103.06]	2614.22[1125.66 4102.78]	2772.61[1412.06 4133.16]

Notes: *** p<0.01, ** p<0.05, * p<0.1, robust standard errors in parentheses. Confidence interval estimates at 95% computed using the delta method are in brackets.

Table D6: Georgia Recreation Trip Demand Model (Full Travel Cost: Assumed Driving Travel Cost) With Subjective Norms

Dependent variable: number of trips (i.e., number of actual and cancel planned trips)

Variables	Poisson	Negative Binomial	Random Effects Poisson	Random Effects Negative Binomial
Full travel cost	-0.00135***	-0.000956***	-0.000956***	-0.000908***
	(0.000306)	(0.000276)	(0.000276)	(0.000194)
Risk perception	0.0347	0.0342*	0.0342*	0.0331**
	(0.0247)	(0.0205)	(0.0205)	(0.0165)
Subjective norms	0.0327**	0.0226*	0.0226*	0.0271**
	(0.0137)	(0.0126)	(0.0126)	(0.0114)
Travel party	-0.00175	0.00564	0.00564	0.00521
	(0.0115)	(0.00941)	(0.00941)	(0.00879)
Overnight trips	-0.673***	-0.634***	-0.634***	-0.573***
	(0.0472)	(0.0435)	(0.0435)	(0.0330)
Income	0.000002***	0.000002***	0.000002***	0.000002***
	(0.0000006)	(0.0000005)	(0.0000005)	(0.0000004)
Age	-0.00735***	-0.00612***	-0.00612***	-0.00513***
	(0.00253)	(0.00220)	(0.00220)	(0.00176)
Female	-0.164***	-0.139***	-0.139***	-0.115***
	(0.0557)	(0.0492)	(0.0492)	(0.0414)
With children	-0.109	-0.110*	-0.110*	-0.0926*
	(0.0677)	(0.0592)	(0.0592)	(0.0493)
Post-COVID	-0.745***	-0.716***	-0.716***	-0.587***
	(0.0461)	(0.0444)	(0.0444)	(0.0348)
Wave dummy = 2	0.139***	0.158***	0.158***	0.0913**
	(0.0519)	(0.0471)	(0.0471)	(0.0376)
Wave dummy = 3	0.630***	0.616***	0.616***	0.503***
	(0.0797)	(0.0724)	(0.0724)	(0.0655)
Constant	2.530***	2.371***	2.371***	2.677***
	(0.195)	(0.160)	(0.160)	(0.135)
Observations	2,662	2,662	2,662	2,662
Log likelihood	-9889.17	-6953.96	-6953.96	-6829.22
AIC	19804.35	13935.91	13935.91	13688.44
BIC	19880.88	14018.33	14018.33	13776.74
CS per trip	742.54[411.97 1073.10]	1045.69[453.83 1637.54]	1045.69[453.94 1637.43]	1100.74[572.56 1628.92]
CS (pre-COVID)	3325.38[1844.97 4805.80]	4682.98[2032.43 7333.54]	4682.98[2032.92 7333.04]	4929.53[2564.14 7294.91]
CS (post-COVID)	1496.60[830.33 2162.86]	2107.59[914.70 3300.48]	2107.59[914.92 3300.26]	2218.55[1154.00 3283.10]
CS (diff pre- & post-COVID)	1828.79[1014.64 2642.94]	2575.39[1117.73 4033.06]	2575.39[1118.001 4032.79]	2710.98[1410.14 4011.82]

Notes: *** p<0.01, ** p<0.05, * p<0.1, robust standard errors in parentheses. Confidence interval estimates at 95% computed using the delta method are in brackets.

CHAPTER 4

ECONOMIC IMPACT ANALYSIS OF COVID-19 ON THE STATE OF GEORGIA ECONOMY: A PERSPECTIVE FROM CANCELED RECREATIONAL TRIPS[11]

[11]Ojo, K. E., Ferreira, S., Salazar, J., Bergstrom, J., & Woosnam, K. M. To be submitted to *Journal of Southern Agricultural Economics*

4.1 Abstract

Nearly all sectors worldwide have been negatively affected by the COVID-19 pandemic. For example, the tourism sector of the state of Georgia's economy, which generated 478,000 jobs and $3.4 billion in state and local tax revenue in 2018, experienced considerable negative impact. COVID-19 resulted in a loss of $11.8 billion in tourism spending and 72,900 jobs in 2020. Given the significance of this pandemic, understanding the impacts of COVID-19 on a regional basis, such as state impacts, will help local and state policymakers develop strategies to enhance recovery from the COVID-19 pandemic and any future similar occurrence. This study analyzes the economic growth and interdependence of canceled and postponed leisure trips due to COVID-19 on the state of Georgia economy. The economic impact analysis was completed using an input-output (I-O) model with impact analysis for planning (IMPLAN). The results showed that canceled leisure trips to Georgia yielded a reduction of approximately $9.03 million in total output for day trips and $30.51 million for overnight trips.

Keywords: economic impact, economic interdependence, IMPLAN, COVID-19 pandemic

4.2 Introduction

Tourism is an important industry in the state of Georgia's economy. In 2018, Georgia tourism generated 478,000 jobs and $3.4 billion in state and local tax revenue, and the state had 111.7 million visitors that generated $36.9 billion in revenue (Explore Georgia, 2020a). However, the travel restrictions due to COVID-19 led to cancellations and closures of travel and hotels, campsites, etc. Subsequently, there was a loss in tourism spending of $11.8 billion and of 72,900 jobs supported by the tourism industry in Georgia in 2020 (Explore Georgia, 2021a). In the tourism industry, the hotels and lodging sector suffered the hardest (Explore Georgia, 2021a), as 70% of hotel employees were laid off or furloughed at the onset of the pandemic in 2020 (AHLA, 2020).

Several studies have studied the impact of COVID-19 on the tourism industry (Gössling et al., 2020; Lee & Chen, 2020; Ojo et al., 2022; Watson & Deller, 2021; Woosnam et al., 2021). Most of these studies have focused on behavioral travel change, the impact on travel and tourism stock returns, and outdoor recreation (Bae & Chang, 2020; Im et al., 2021; Landry et al., 2021). For their analysis, several of these studies utilized country-level and intercountry data, while a few others used regional economic data (Landry et al., 2021; Neuburger & Egger, 2021; Salazar et al., 2020; Suse et al., 2021; Villacé-Molinero et al., 2021; Wu et al., 2022). For example, Wu et al. (2022) used a pre- and postpandemic comparison to analyze the impacts of the COVID-19 outbreak on the economic contribution of domestic tourism in China. Salazar et al. (2020) used a quick approach with data on job losses to estimate the impact of COVID-19 on the state of Georgia economy. Han et al. (2022) used employment and wage change data to examine the impacts of COVID-19 on tourism and the hospitality sector, finding that rural counties experienced fewer negative job growth impacts of COVID-19.

Given the significant contributions of tourism to the Georgia economy and the negative impacts of COVID-19 on this sector, additional information on the significance of COVID-19 to the state of Georgia's economy will help local and state policymakers develop strategies to enhance recovery from the COVID-19 pandemic. Information on how the pandemic has affected different industry sectors and the economy is of utmost importance to tourism and travel stakeholders. A focus on understanding the impacts of COVID-19 on a regional basis (such as state impacts) is essential, couple with the increased interest in regional economic impact analysis of recreation commodities (Bergstrom et al., 1990; Sardana et al., 2016). Therefore, this study focused on how canceled and postponed leisure trips to Georgia due to COVID-19 affected the state economy in 2020. Specifically, we estimated the economic growth and interdependence effects of canceled and postponed leisure trips due to COVID-19 on the state of Georgia economy. The economic impact analysis was completed using an input-output (I-O) model with impact analysis for planning (IMPLAN).

The remaining sections of this chapter are as follows: Section 4.3 describes the methodology, i.e., the economic growth and interdependence analysis in IMPLAN and the data used. Section 4.4 explains the study results, while Section 4.5 illustrates the study implications and conclusions.

4.3 Methodology

4.3.1 Estimation of Economic Impact

4.3.1.1 Economic Growth and Economic Interdependence

The economic growth impact of canceled/postponed recreation trips represents the distributional economic effect of canceled recreational trips on the state of Georgia's economy by Georgia nonresidents. Specifically, the expenditure by nonresident visitors to Georgia represents "new" money (i.e., outside dollars) brought into the state economy, boosting total wealth in the economy and thereby, leading to economic growth. The economic growth impacts were quantified by measuring the changes in total output, employment, and income. The economic impact estimation was computed by capturing the direct, indirect, and induced effects of intended spending for canceled and postponed recreational trips on the state of Georgia. The direct effect is the total intended spending that tourists were supposed to spend in Georgia had recreational trips not been canceled. The indirect effect was the “ripple effects” of tourist spending as expenditure on secondary inputs to meet tourists’ demand for goods and services. The added economic activity resulting from direct and indirect effects of Georgia tourist spending resulting in increased income for the local economy, such as increased household income, wages, and business profits, were the induced effects. The direct, indirect, and induced effects of the economic growth and interdependence were also computed.

Economic interdependence, as defined by Cordell et al. (1992), “measures the overall interrelationships between the pattern and level of recreationist’s spending (resident and non-resident) and the pattern and the level of economic activity in the region” (p. 254). Economic interdependence analysis does not focus on economic growth. However, it acknowledges that the portion of results impacted by tourist spending is a redistribution of monetary resources that already exist within the region. Nevertheless, some percentage of resident spending can account for economic growth under rare circumstances (Cordell et al. 1992). Hence, combining expenditure by residents and nonresidents of Georgia helps us estimate the total interdependence of canceled and postponed recreational trips with the industries and businesses in Georgia’s economy. High interdependence implies that recreation is essential to Georgia’s economy, and the resultant effect of canceled and postponed recreation/leisure trips due to COVID-19 could thus have striking effects on Georgia's economy.

This study estimated the direct, indirect, and induced effects using IMPLAN, a common and widely used tool for computing I-O models. It is primarily designed to measure economic impact analysis and has been used since 1979 (U.S. Forest Service, 1993). It has been widely used to estimate tourism and recreation activities (Bowker et al., 2007; Loomis & Caughlan, 2006; Salazar et al., 2020).

4.3.2 Data

Estimating the changes to final demand resulting from canceled/postponed intended recreation/leisure trips to Georgia involves assessing the number of canceled/postponed trips, the mean expenditure per canceled/postponed trip, and the allocation of the total canceled/postponed trip expenditure across IMPLAN economic sectors within the state of Georgia.

4.3.2.1 Expenditure and Canceled Trips Data Information

Estimating the final demand changes from canceled/postponed recreation trips requires expenditure data of visitors to Georgia (nonresident visitors for the economic growth analysis; a combination of Georgia resident and nonresident visitors for the economic interdependence analysis). Therefore, we used survey data collected via Qualtrics across two waves, i.e., two different times, to obtain data on Georgia's visitor[12] expenditure. Survey links were sent to the email addresses of Georgia visitors provided by Explore Georgia (an arm of the Georgia Department of Economic Development in charge of tourism research and management). The purpose of the survey was to collect data on travel sentiments and behavior during COVID-19.

[12] Georgia visitors refers to visitors to Georgia for nonresidents and visitors within Georgia for residents.

Respondents were asked questions about whether they had canceled or postponed intended leisure trips to Georgia or within Georgia due to the COVID-19 threat in 2020. The respondents who had canceled or postponed leisure trips were asked to provide further information on their intended expenditure for the trips they had canceled or postponed. The expenditure item for respondents was based on the following categories: *Transportation (at your final destination for gas, taxi, etc.)*, *lodging (hotel/motel/inn/rental home)*, *food and beverage dining out*, *food and beverage groceries*, *retail purchases (clothing, souvenirs, etc.)*, and *recreation/entertainment (activities, attractions, special events, tours, etc.)*. The above survey questions were asked separately for day and overnight trips.

The survey was conducted for wave 1 between June 25 and July 28, 2020 and wave 2 from October 19 to November 17, 2020. A total of 2576 observations for day and overnight trips. We further cleaned the data by dropping respondents whose origins were outside the United States and those whose destinations were outside of Georgia. Therefore, after the data cleaning, we had 1044 observations for Georgia visitors who canceled/postponed recreational trips to (within) Georgia in 2020 for nonresidents and residents. Among Georgia nonresidents, 134 responded regarding day trips and 175 regarding overnight trips. For combined Georgia residents and nonresidents, day trips totaled 634 respondents, while overnight trips totaled 410 respondents. The mean expenditure per person per trip for each category of expenditure items and trip types were estimated.

The total number of leisure visits to Georgia in 2019 and 2020 were provided by Explore Georgia. Because we do not have the number of canceled leisure trips in 2020, we used a proxy and made assumptions, such that the difference between the number of taken leisure trips in 2019 and 2020 were assumed to be trips not taken due to COVID-19 (i.e., the taken leisure trips in 2019 were higher compared to 2020) (Explore Georgia 2020b; Explore Georgia 2021a; Explore Georgia

2021b). Leisure taken trips for 2019 and 2020 and the differences between the trips in 2019 and 2020 are shown in Table 4.1.

4.3.2.2 IMPLAN Sector Data Allocation and Final Demand Changes

IMPLAN is a software application containing an annual national and regional database that can be used to construct I-O models for specific regions (state or county). IMPLAN can predict how specific economic changes will affect a given national or regional economy or analyze the impact of existing or past economic activities (Bergstrom et al., 1990; Clouse, 2019a). IMPLAN can be used to compute the direct, indirect, and induced effects of final demand changes. Previous studies in tourism and recreation have used the IMPLAN I-O model to estimate the impacts of recreation trails on the specific regional economy and the economic changes in a region's economic activity (Bowker et al., 2007; Loomis & Caughlan, 2006; Salazar et al., 2020).

I-O modeling in IMPLAN for the regional economic impacts of recreation is quite flexible. Bergstrom et al. (1990) highlighted one difficulty when using the I-O model in IMPLAN, which is “determining how recreational expenditures translates into changes in final demand for outputs produced in a regional economy” (p. 70). In this study the regional economy is the state of Georgia.

Expenditure data collected for each item, such as transportation, food, and beverage dining out, food and beverage groceries, retail purchases, recreation/entertainment, and lodging, were linked in IMPLAN to industry sectors using the trip characteristics reported by Explore Georgia in 2020 for day and overnight trips. The report included individual characteristics for day and overnight, the mode of transportation visitors used to commute around Georgia, the types of recreational activities in which they engaged, shopping types on the trip, dining types on the trip, and accommodations type.

Table 4.1: Summary of Leisure Trips by Visitors to Georgia in 2019 and 2020

Number of leisure trips taken by visitors to Georgia in 2019 and 2020

	2019		2020	
	Day trips	Overnight trips	Day trips	Overnight trips
Taken leisure trips by combined Georgia residents and nonresidents	27,356,666.67	19,328,571.43	25,670,714.29	16,373,636.36
Taken leisure trips by Georgia nonresidents	13,404,766.67	14,109,857.14	13,348,771.43	11,625,281.82

The difference in the number of leisure trips between 2019 and 2020

	Day trips	Overnight trips
Difference in taken leisure trips by combined GA residents and nonresidents	-1,685,952.38	-2,954,935.06
Difference in taken leisure trips by GA nonresidents	-55,995.24	-2,484,575.32

The taken leisure trips figure is the author’s estimation from Georgia tourism industry data provided by Explore Georgia. The data were taken from reports on USA travel visitor profiles prepared by Longwoods International for day and overnight trips in 2019 and 2020. We assumed the difference between the number of leisure trips taken to Georgia in 2019 and 2020 to be trips canceled (not taken) due to COVID-19.

The proportions of how visitors engaged or used each of the expenditure items were reported by Explore Georgia (Explore Georgia 2021a; Explore Georgia 2021b), while we normalized the proportions to a 100% ratio. Clouse (2019b) provided details information on IMPLAN sectors using the 2017 North American Industry Classification System (NAICS) to IMPLAN 546 Industries. This detailed information on IMPLAN sector description was used to construct a bridge table (presented in Appendix Table A1). The final demand changes were allocated to the IMPLAN sectors using the normalized proportion from the Explore Georgia report.

Final demand changes were computed by multiplying the mean expenditure per person per trip by the number of canceled/postponed leisure trips to Georgia. The economic impacts of canceled trips were estimated by entering the final demand changes values presented in Appendix Table A1 for each industry sector as the "event". IMPLAN model estimated the changes in employment, labor income, value added, and output in each sub-sector associated with the expenditure of canceled/postponed trips.

4.4 Results

4.4.1 Expenditure Profile

Table 4.2 presents the computed values of tourist expenditure profiles in 2020 for day and overnight trips for only Georgia nonresidents and separately for the combination of Georgia residents and nonresidents. Columns 1–4 show the mean expenditure per trip for Georgia nonresidents for day and overnight trips. The mean expenditure per person per trip for day trips (column 2) was \$20.38 for transportation, \$29.25 for food and beverage dining out, \$11.50 for food and beverage groceries, \$15.36 for retail purchases, and \$21.25 for recreation.

Columns 5–6 show the mean expenditure per trip for combined residents and nonresidents for day and overnight trips. The expenditure item with the highest value for day trips was food and beverage dining out ($16.42 per person per trip), followed by recreation ($13.13 per person per trip). For overnight trips, the expenditure item with the highest value was lodging ($90.90 per person per trip).

The final demand changes were computed by multiplying the mean expenditure per person per trip by the number of canceled trips to Georgia. The final demand changes were estimated as negative values because canceled trips were considered as lost trips, and the demand values are a loss to Georgia economy. Thus, the final demand values were allocated to IMPLAN sectors using the methods explained in the IMPLAN data allocation section above.

4.4.2 Number Canceled Trips Estimates

The estimated number of trips canceled to the state of Georgia in 2020 was computed using the Explore Georgia day and overnight visitors' profiles for 2019 and 2020. Explore Georgia reported the total person-trips[13], size of the travel party, percentage of trips for residents and nonresidents, and percentage for trips to leisure, business, and business-leisure (i.e., a hybrid where the primary purpose of a trip is business but is extended to include a leisure component). Therefore, the number of trips taken in 2019 and 2020 were estimated as the number of total person-trips divided by the size of the travel party for both day and overnight trips. The number of taken trips in 2019 and 2020 for day and overnight trips was further broken into leisure, business, and business-leisure trip categories. The number of leisure trips taken in 2019 for day and overnight trips was higher than in 2020; we associated this decrease in leisure trips in 2020 with COVID-19. Thus, we assumed that the reduction in leisure trips in 2020 is canceled trips (i.e., trips not taken) due to COVID-19.

[13] Total person-trip is any trip made by a single traveler to Georgia in 2019 and 2020, which means the same person can be counted multiple times if they make multiple trips. It also accounts for travel party size. For example, in 2019, if a family of 4 traveled overnight to (within) Georgia, then returned home and repeated the trip on a separate occasion, that would count as 8 overnight person-trips to the state of Georgia (2 trips, 8 person-trips) in 2019.

Table 4.2: Expenditure Profiles by Tourists Group for 2020

Expenditure Item	Nonresidents				Combined residents and nonresidents			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Entire group (day trips)	Per person per trip (day trips)	Entire group (overnight trips)	Per person per trip (overnight trips)	Entire group (day trips)	Per person per trip (overnight trips)	Entire group (overnight trips)	Per person per trip (overnight trips)
	(N = 134, spending party = 2.68)		(N = 175, spending party = 2.07)		(N = 634, spending party = 2.48)		(N = 410, spending party = 2.23)	
	($)	($)	($)	($)	($)	($)	($)	($)
Transportation	43	20.38	96.1	46.43	26	10.48	63.96	28.68
Food and Beverage Dining Out	61.72	29.25	140.67	67.96	40.71	16.42	116.7	52.33
Food and Beverage Groceries	24.26	11.5	56.1	27.1	14.14	5.7	46.96	21.06
Retail Purchase	32.4	15.36	55.67	26.89	20.7	8.35	43.55	19.53
Recreation/Entertainment	44.84	21.25	70.51	34.06	32.56	13.13	66.98	30.04
Lodging	0	0	233.1	112.61	0	0	202.71	90.9
Total	206.22	97.74	652.15	315.05	134.11	54.08	540.86	242.54

Table 4.3: Final Demand Changes Estimates

Expenditure Item	Final demand changes for nonresidents (million $)		Final demand changes for combined residents and nonresidents (million $)	
Transportation	-1.14	-2.60	-17.67	-48.35
Food and Beverage Dining Out	-1.64	-3.81	-27.68	-88.23
Food and Beverage Groceries	-0.64	-1.52	-9.61	-35.51
Retail Purchase	-0.86	-1.51	-14.08	-32.93
Recreation/Entertainment	-1.19	-1.91	-22.14	-50.65
Lodging	-	-6.31	-	-153.25

Total	-5.47	-17.64	-91.18	-408.91

The authors estimate the mean expenditure per person per canceled trip and the total number of canceled trips in 2020. The final demand changes are equal to the mean expenditure per person per canceled trip multiplied by the total number of canceled trips

Table 4.4: Economic Impacts of Expenditure by Visitors Who Canceled Trips to Georgia in 2020 on State Economy

	Economic Indicators							
Impact	Employment	Labor Income (million $)	Value Added (million $)	Output (million $)	Employment	Labor Income (million $)	Value Added (million $)	Output (million $)
	Economic Growth (Day trips)				Economic Growth (Overnight trips)			
1 - Direct	-109.75	($1.70)	($2.25)	($4.36)	-302.68	($6.36)	($9.20)	($15.54)
2 - Indirect	-13.57	($0.77)	($1.35)	($2.51)	-41.14	($2.36)	($3.97)	($7.34)
3 - Induced	-13.99	($0.66)	($1.26)	($2.16)	-49.34	($2.34)	($4.46)	($7.63)
TOTAL	-137.31	($3.14)	($4.86)	($9.03)	-393.17	($11.07)	($17.63)	($30.51)
	Economic Interdependence (Day trips)				Economic Interdependence (Overnight trips)			
1 - Direct	-1,782.07	($28.46)	($37.57)	($72.59)	-6,567.85	($149.83)	($216.90)	($361.26)
2 - Indirect	-226.98	($12.84)	($22.35)	($41.89)	-945.87	($53.89)	($90.27)	($167.69)
3 - Induced	-233.63	($11.10)	($21.10)	($36.13)	-1,152.47	($54.77)	($104.10)	($178.26)
TOTAL	-2,242.69	($52.41)	($81.03)	($150.61)	-8,666.18	($258.48)	($411.27)	($707.22)
	Percentage of Interdependence Quantified for Nonresidents (day trips)				Percentage of Interdependence Quantified for Nonresidents (overnight trips)			
	6.12	5.99	6.00	6.00	4.54	4.28	4.29	4.31

Table 4.1 shows the number of leisure trips taken in 2019 and 2020 and the difference between them for day and overnight trips and as categorized into nonresidents and combined residents and nonresidents. The total number of leisure trips taken within (to) the state of Georgia by combined residents and nonresidents in 2019 was approximately 27.4 million day trips and 19.3 million overnight trips. In 2020, the number of taken trips was approximately 25.7 million day trips and 16.4 million overnight trips. The differences between the numbers of day and overnight trips were approximately 1.7 million and 2.95 million, respectively.

4.4.3 Total Economic Impacts and Interdependence Estimates

The economic growth impact estimates of canceled leisure trips due to the COVID-19 pandemic on the state of Georgia's economy in 2020 for day and overnight trips are presented in Table 4.4. The direct, indirect, and induced effects on employment, labor income, value-added, and output associated with economic growth impact are also reported in Table 4.4. The economic impacts associated with nonresidents' spending on canceled/postponed day trips resulted in a reduction of 137 jobs, $3.14 million in total labor income, and $4.86 million in total output in 2020. For overnight trips, the economic growth impact resulted in a loss of 393 jobs, $11.07 million in labor income, $17.63 million in value added, and $30.51 million in output.

The economic interdependence analysis results are shown in the lower section of Table 4.4. These results indicated that canceled leisure trips negatively affected the state of Georgia's economy. They also showed the degree of interdependence between spending related to canceled trips by visitors to Georgia and business activity by Georgia firms and industries. The total gross output reduction due to expenditures associated with canceled trips was $150.61 million (day trips) and $707.22 million (overnight trips). Labor income was reduced by $52.41 million for day trips and $258.48 million for overnight trips. The total number of jobs (or employment) lost was 2,243 for day trips and 8,666 for overnight trips.

The economic multipliers displayed in Table 4.5 show the potential economic impacts of nonresident canceled trip expenditures in Georgia. The multiplier is the ratio of the sum of direct, indirect, and induced effects to direct effects, i.e., the ratio of total effects to direct effects. The multiplier for employment was 1.25, the total value added was 2.16, and the total output was 2.07 for day trips. For overnight trips, the multiplier for employment was 1.30, the total value added was 1.92, and the total output was 1.96. These multiplier values are relatively high, indicating that the impact of canceled trips by Georgia nonresidents exerted enormous adverse effects on economic growth.

Table 4.5: Multipliers

	Day trips	Overnight trips
Employment	1.25	1.30
Total Value Added	2.16	1.92
Total Output	2.07	1.96

4.5 Discussion, Implications, and Conclusion

The study in this paper provides an economic growth and interdependence analysis of canceled and postponed leisure trips due to COVID-19 on the state of Georgia's economy. The economic growth and interdependence analysis showed negative impacts of COVID-19 (resulting in canceled or postponed leisure trips to and within Georgia) for day and overnight trips in 2020. These results are consistent with several studies that have shown the negative impacts of COVID-19 on several sectors, especially in the travel and tourism industry (Gössling et al., 2020; Im et al., 2021; Salazar et al., 2020). Economic growth and economic interdependence analysis using day and overnight expenditure data associated with canceled and postponed leisure trips could provide tourism and travel stakeholders and policymakers in Georgia with insights into the differences between the economic impact generated for residents and nonresidents for day and overnight trips, thus enabling them to design policies that could enhance recovery strategies for the Georgia tourism industry.

Previous studies examining the economic impacts of COVID-19 have used a quick approach (Salazar et al., 2020), such as using data covering only a few months. However, in this study, we used two waves of data, which better captures the impacts of COVID-19 that resulted in canceled trips. The economic growth results showed that the negative impact of canceled trips on the Georgia economy was higher for overnight trips than day trips. For example, the total jobs lost due to canceled and postponed trips was 137 for day trips, while for overnight trips, it was 393. These results were higher for overnight trips because trips canceled for overnight purposes included lodging expenditure.

Such economic interdependence resulted in canceled trip expenditures, thereby negatively affecting the degree and distribution of goods, employment, income, and other economic attributes of the Georgia state economy. The results of economic interdependence analysis further suggested that expenditures associated with canceled and postponed leisure trips was significantly interrelated with the economic activities of industries and firms in the Georgia state economy. Moreover, some aspects of economic interdependence included some economic growth, since the analysis also considered nonresidents.

The study presented in this paper found a multiplier ranging between 1.25 and 2.16. Multiplier results for the economic impacts were somewhat high. The multiplier was compared with previous studies on the economic impact analysis of recreation/leisure trips to parks and trails around the United States. Our multiplier values are relatively close to those: For example, the multiplier in Bergstrom et al. (1990) associated with recreational visits to Georgia ranged between 1.85 to 2.10; Cordell et al. (1992) found a multiplier for Kansas between 1.66 and 2.92; and the study by Bowker et al. (2007) on the economic impacts of Virginia Creeper recreational trail visits on Washington and Grayson counties ranged between 1.00 to 1.44.

One limitation of this study is that a relatively small sample size was used in the analyses of nonresidents for day and overnight trips. Another limitation of this study is that respondents might have either overestimated or underestimated their expenditure values regarding their intended but canceled trips. Although this study has limitations, the results can guide tourism and travel stakeholders and policymakers in Georgia through the ongoing recovery from the COVID-19 pandemic by developing marketing strategies that encourage tourists to choose Georgia and consequently improve the state of Georgia economy through tourism.

Finally, this study contributes to the growing literature on COVID-19 by providing specific information regarding the economic impact of trips canceled and postponed due to COVID-19 on the Georgia state economy, rather than the overall economic impacts of COVID-19 provided by Explore Georgia and other economic attributes that have been previously considered in the literature, such as using the loss-of-employment data in economic impact analysis. To the knowledge of the authors, this study is one of the few studies to estimate economic impacts with canceled trips data. With more information available on the economic impacts of COVID-19 on several industry sectors, policymakers can develop a quicker and more insightful approach as the world continues to recover from the COVID-19 pandemic.

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Chapter 4 Appendices: Appendix A, Bridge Table

Table A1: Survey expenditure item description, linked with Explore GA expenditure descriptions then with IMPLAN sectors descriptions

					Final demand changes into the categories of industry sectors			
					Nonresidents		Combined residents and nonresidents	
Expenditure Item		IMPLAN Industry sector	Day trips (%)	Overnight trips (%)	Day trips (million $)	Overnight trips (million $)	Day trips (million $)	Overnight trips (million $)
Lodging								
	507	Hotels and motels, including casino hotels	-	50.00	-	-3.15	-	-76.63
	508	Other accommodations	-	50.00	-	-3.15	-	-76.63
		Total	-	100.00	-	-6.31	-	-153.25
Transportation								
	414	Air transportation	6.90	6.90	-0.08	-0.18	-1.22	-3.33
	415	Rail transportation	5.91	5.91	-0.07	-0.15	-1.04	-2.86
	416	Water transportation	4.93	4.93	-0.06	-0.13	-0.87	-2.38
	418	Transit and ground passenger transportation	82.27	82.27	-0.94	-2.14	-14.54	-39.78
		Total	100.00	100.00	-1.14	-2.60	-17.67	-48.35
Food Beverage and dining out								
	509	Full-service restaurants	56.19	48.91	-0.92	-1.86	-15.56	-43.15
	511	All other food and drinking places	43.81	51.09	-0.72	-1.94	-12.13	-45.08
		Total	100.00	100.00	-1.64	-3.81	-27.68	-88.23
Food and Beverage Groceries								

	406	Retail - Food and beverage stores	100.00	100.00	-0.64	-1.52	-9.61	-35.51
Retail Purchases								
	411	Retail - General merchandise stores	57.93	53.67	-0.50	-0.81	-8.16	-17.67
	412	Retail - Miscellaneous store retailers	42.07	46.33	-0.36	-0.70	-5.92	-15.25
		Total	100.00	100.00	-0.86	-1.51	-14.08	-32.93
Recreation/Entertainment								
	501	Museums, historical sites, zoos, and parks	34.29	37.76	-0.41	-0.72	-7.59	-19.12
	504	Other amusement and recreation industries	55.71	48.98	-0.66	-0.93	-12.33	-24.81
	505	Fitness and recreational sports centers	10.00	13.27	-0.12	-0.25	-2.21	-6.72
		Total	100.00	100.00	-1.19	-1.91	-22.14	-50.65

CHAPTER 5

CONCLUSION

This dissertation developed a conceptual framework for two different theoretical models on individual behavior in the context of recreation and tourism related to COVID-19. Undoubtedly, COVID-19 has negatively impacted nearly all sectors worldwide, with tourism being one of the hardest hit (U.S. Travel Association, 2022). An extensive understanding of these impacts will significantly improve recovery strategies and policy by tourism stakeholders and policymakers. The three essays presented in this dissertation provide methodological improvements to behavioral models and insights into the impacts of COVID-19 on the tourism and travel industry.

In the first essay, we developed a new model – extended expected utility theory (EUT) – to explain human behavior regarding leisure travel by combining EUT and the theory of planned behavior. We used the EUT and extended EUT models to examine the factors influencing individuals to cancel or postpone intended or planned leisure trips in the United States amid COVID-19. Our results showed that the proposed extended EUT model performed better than EUT using model selection criteria such as the Akaike information criterion and Bayesian information criterion. The results also showed that risk perception is the most crucial factor influencing individual decisions. Our in-depth examination of the nature of risk perception showed that health risk was more essential than financial risk when an individual in the United States canceled/postponed leisure travel.

In the second essay, we developed a conceptual framework to explain the effects of subjective norms on environmental commodity valuation. We empirically tested these effects using data on the impacts of the COVID-19 pandemic on tourists' decisions to take or cancel trips to the state of Georgia. In the empirical analysis, we used the travel cost recreation demand model. We analyzed the data using Poisson, negative binomial, random effects Poisson, and random effects negative binomial count data models. The data used in the analysis were survey data collected through Qualtrics across three waves in 2020 and 2021 among Georgia visitors within the United States to measure their travel sentiments amid COVID-19. The study results showed that the subjective norms variable was a statistically significant recreation demand shifter. We estimated a net decrease of approximately 1,800 in consumer surplus (CS) or WTP for visitors to Georgia associated with COVID-19.

In the third essay of this dissertation, we further delved into the impacts of COVID-19 on tourism by conducting an economic growth and interdependence analysis, i.e., an economic impact analysis of canceled or postponed leisure trips due to COVID-19 on the state of Georgia's economy. The impact analysis was performed using the input-output model with IMPLAN. The results showed that the economic impacts of COVID-19, based on canceled/postponed trips to Georgia, led to reductions in total output by $9.03 million for day trips and $30.51 million for overnight trips. Furthermore, the impact results showed a decrease of $3.14 million and $11.07 million in labor income for day and overnight trips, respectively.

The results of the three essays are consistent with previous literature. For example, in essay one, we found risk perception and subjective norms to be partial determinants of why tourists canceled/postponed intended recreation/leisure trips within the United States. This result was consistent with studies on travel intention and vacation travel behavior change during the pandemic (Bratić et al., 2021; Falahuddin et al., 2020; Neuburger & Egger, 2020; Perić et al., 2021). Moreover, the negative impact of COVID-19 on recreation demand and value shown in essay two was consistent with the results of Landry et al. (2021) regarding the effects of COVID-19 on outdoor recreation. The reductions in output, labor income, and value added of canceled/postponed intended leisure trips on the state of Georgia economy during the pandemic were consistent with studies on the impact of COVID-19 on tourism sectors within the United States (Huang et al., 2020; Salazar et al., 2020).

The conceptual model developed in essays one and two is not limited to the COVID-19 pandemic situation. For example, the proposed extended EUT model developed in essay one can be applied in other tourism contexts and in studies that involve measuring human behavior in decisions involving risk and uncertainty. The model can be implemented and used when tourists face risks and uncertain outcomes in deciding to travel during, for instance, natural disasters, terrorism, and times of war. In addition, the conceptual models developed in essay two to estimate recreation demand models that account for subjective norms can be used to assess other recreation demand models of environmental commodities, such as recreational boating, fishing, and hunting.

Nevertheless, the essays included in this dissertation are not without limitations. As beneficial as data collected in waves are to research studies on human behavior, this approach also does have its limitations. For example, the data were collected through a survey, resulting in the possibility that individuals over- or underestimated their previous or planned or intended canceled travel expenditures. Such limitations notwithstanding, this dissertation answers crucial questions related to COVID-19 and tourism related to consumers across the United States and the state economy of Georgia. The results can aid decision making on strategies to recover from the COVID-19 pandemic. Additionally, the proposed models contribute to the decision-theoretic and environmental valuation literature and the growing literature on COVID-19.

5.1 References

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