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Evaluating Travel Behavior Resilience across Urban and Rural Areas during the COVID-19 Pandemic: Contributions of Vaccination and Epidemiological Indicators

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ABSTRACT: The COVID-19 pandemic has severely disrupted travel behavior across diverse socio-economic areas, with a significant impact on transportation systems, public health, and the economy. As countries both recover and plan for future virus-driven stresses, it is crucial to identify the drivers of building travel behavior resilience, such as vaccination. Using an integrated dataset with over 150 million US county-level mobile device data from 01/01/2020 to 20/04/2021, we employ Bayesian structural time series (BSTS) models to infer the relative impact of the vaccination intervention on five types of travel behavior across Metropolitan, Micropolitan and Rural areas. Further, we develop partial least squares regression (PLSR) models to accurately estimate how COVID-19 vaccination rates, epidemiological indicators (i.e., COVID-19 incidence rates, death rates, and testing rates) and weather conditions (i.e., temperature, rain, and snow) would impact various travel behaviors across the diverse areas during the recovery period of the pandemic. The model results shed light on the positive role of vaccinations in fostering the recovery of travel behaviors and reveal the disparities in travel behavior resilience in response to vaccination rates, epidemiological indicators, and weather conditions across diverse areas. Our findings can offer evidential insights for policymakers, transport planners, and public health officials, guiding the development of equitable, sustainable, and resilient transportation systems prepared to adapt to future pandemics.

KEY WORDS: ***COVID-19, Travel behavior resilience, Vaccination, COVID-19 epidemiological indicators, Bayesian structural time series (BSTS), Partial least squares regression (PLSR)***

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1. Introduction

The coronavirus disease 2019 (COVID-19) pandemic has significantly affected human travel behavior. Initially, countries implemented various nonpharmaceutical interventions (NPIs) such as quarantine, stay-at-home orders, and social distancing to mitigate the impact of the virus. Thereafter, widespread vaccination has emerged as a key strategy to combat the virus and restore normalcy, reducing the severity of illness, hospitalizations, and deaths. As countries started to recover from the pandemic, combining NPIs and vaccination efforts offered a multi-layered approach to enhance the recovery and resilience of travel behavior, instilling confidence in travelers and supporting the revival of human mobility (Doroshenko, 2021). It is shown that a higher vaccine coverage, even with lower vaccine effectiveness, would lead to a significant decrease in infections, the cumulative incidence of infections, hospitalizations, and deaths varied by ethnicity, race, and place of residence, with African American persons and rural residents faring the worst (Patel et al., 2021).

COVID-19 epidemiological indicators, such as COVID-19 incidence rates, death rates, and testing rates, play a crucial role in determining travel restrictions, quarantine requirements, and other NPIs set by authorities and thus directly impact individual's travel behavior (Chan et al., 2020). Rural and urban areas differ in various aspects, including population density, healthcare resources, transportation infrastructure, and socio-economic factors, and these distinctions have an impact on the human mobility response to COVID-19 epidemiological indicators (König & Dreßler, 2021). Therefore, mobility response to the impact of COVID-19 resulting from both individual responses and government interventions exhibited significant variations across rural and urban areas. Gauvin et al. (2021) studied the relationships among demographic, economic, and epidemiological variables and suggested that the most influential socio-economic factors explaining

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different mobility responses across these areas are tied to the local labor force structure. For example, a significant portion of rural respondents kept their pre-pandemic travel habits during the pandemic due to essential work and activities in a rural context (König & Dreßler, 2021). COVID-19 has had negative short-term impacts on rural societies, however, in the long run, there may be opportunities for changes in mobility behaviors, driven by modified work and activity patterns (Nelson & Caulfield, 2022).

Existing literature in transport has evaluated the impact of COVID-19 on travel behavior changes, such as public transport ridership (Hu & Chen, 2021), public transport use (Hsieh, 2023; Wang et al., 2022), working from home (WFH) preferences (Beck & Hensher, 2022; Hensher et al., 2023), and modal shift from public to private transport modes (Das et al., 2021). In these contexts, "travel behavior resilience" refers to the ability of individuals' or communities' travel patterns to withstand, adapt to, and recover from various disruptions and challenges posed by the COVID-19 pandemic. Yet, unlike previous literature that emphasizes the immediate ramifications of the COVID-19 outbreak, this research specifically investigates the contributions of COVID-19 vaccinations in building the travel behavior resilience. Moreover, it is still unclear how much the vaccination intervention will impact travel behavior resilience, considering the other factors such as COVID-19 epidemiological indicators and weather conditions across urban and rural areas. Our investigation poses the following questions: 1) To what extent does the rollout of vaccinations contribute to the resilience in travel behavior across urban and rural areas? 2) How do individuals' travel behavior correlate with COVID-19 epidemiological indicators, vaccination rates, and weather conditions during the recovery period of the pandemic across urban and rural areas? 3) Which determinants might influence the disparities in travel behavior resilience across urban and rural areas? and 4) What policies should the governments implement to ensure equitable access and resilience of transportation systems and efficient disease containment in future pandemics?

To answer these questions, we first develop Bayesian structural time series (BSTS) models to infer the causal impact of vaccination intervention on five types of travel behavior, considering the impact of epidemiological indicators and weather. Subsequently, we establish partial least squares regression (PLSR) models to estimate the relationship between each travel behavior and vaccination rates, epidemiological indicators, and weather conditions across Metropolitan, Micropolitan and Rural areas[1]. Our analysis draws from an integrated dataset comprising mobile device location data from over 150 million active samples. The five types of daily travel data (i.e., WFH%, work/nonwork trips, out-of-county trips%, and travel miles) were aggregated at the county level with daily COVID-19 vaccination rates, COVID-19 epidemiological indicators, and weather data in the United States (US) during the period from 01/01/2020 to 20/04/2021[2].

The reminder of the paper is organized as follows; Section 2 provides a literature review, identifies research gaps, and summarizes our contributions, Section 3 provides the research framework and methodology, Section 4 provides results analysis, and Section 5 provides policy implication, and Section 6 concludes the study with the suggested future research directions.

2. Literature review and aimed contributions

In this section, we review the literature on the impact of COVID-19 on travel behavior changes (Section 2.1), contributions of NPI and vaccination in travel behavior resilience (Section 2.2), and summarize the research gaps and our contributions (Section 2.3).

2.1 The impact of COVID-19 on travel behavior changes

During the early days of the pandemic, Chinazzi et al.(2020) developed a global metapopulation disease transmission model to examine the impact of travel restrictions on the spread of COVID-19, and confirmed that travel restrictions can effectively reduce the spread of the virus. Beck & Hensher (2020) provided insights into the changes in travel behavior and attitudes in response to COVID-19 in Australia and highlighted the need for ongoing monitoring of these changes as restrictions ease and the country moves towards a 'new normal'. Xiong et al. (2020) found evidence of a positive correlation between human mobility and COVID-19 infections, particularly in regions that had partially reopened. Tirachini & Cats (2020)

[1] US Office of Management and Budget (OMB) defines a metropolitan statistical area as one or more adjacent counties that have at least one urbanized area of 50,000 or more population; a micropolitan statistical area centers around an urban cluster of 10,000 ~ 50,000 people. Rural areas have lower population densities and are often characterized by agriculture, open spaces, and small towns or villages. Specific boundaries and definitions can vary by country, but the OMB has specific criteria for defining these areas based on population and commuting patterns.

[2] The travel behavior data obtained from COVID Impact Platform (Maryland Transportation Institute, 2020) was last updated on April 20, 2021.

investigated the impact of COVID-19 on public transport and highlighted the need for co-ordinated action from policymakers, public transport agencies, workers, and users to ensure that public transport can accommodate and attract more passengers. Gao et al. (2020) statistically quantified the correlations between two human mobility measures (travel distance and stay-at-home time) and the COVID-19 cases across US states, highlighting the importance of human mobility patterns and digital contact tracing.

During the recovery phase, Zhang & Hayashi (2022) reviewed the impacts of COVID-19 on passenger transport, the effectiveness of measures taken to address the impacts, and the adaptation of individuals' travel behavior during the pandemic. Xi et al.(2023) quantified the impact of COVID-19 epidemiological indicators on travel behavior of different socio-economic segments (SES), using integrated mobile device location data in the USA and found that human mobility response to epidemiological indicators in low SES is more sensitive than that in the high SES. For example, the increase in new COVID-19 cases has a significant impact on the number of work trips in the low SES but has little impact on the number of work trips in the high SES. Hu & Chen (2021) proposed a joint framework incorporating time-series prediction, impact inference, and spatial analysis to infer the causal impact of COVID-19 on public transport ridership in Chicago and found that low-income and minority communities were disproportionately affected. Wang et al. (2022) examined the changes in individuals' travel behavior during the COVID-19 pandemic in North Carolina and found that people in the low SES areas (often "essential" workers) continued travelling during the pandemic, highlighting significant disparities in travel behavior among different SESs during the lockdown.

2.2 Contributions of NPI and vaccination on travel behavior resilience

"Resilience" denotes the ability of a system or entity to recover and return to normality following a disruption (Henry & Ramirez-Marquez, 2012). The concept of "resilience" was first coined by Holling (1973) in ecological contexts, and then it has been refined and adopted in transportation systems. In a context of COVID pandanmic, complete recovery indicates that after lockdowns, individuals either revert to their pre-pandemic behaviors or adapt to new interventions such that their behaviors align closely with how they acted before the pandemic. This adaptability in demand corresponds to the concept of "behavioral resilience" in psychology, defined as positive adaptation in the face of socio-economic shifts, traumatic experiences, community sorrow, and environmental stress (Bonanno et al., 2007). Wang et al. (2022) measured "travel behavior resilience" with a "resilience triangle" where the base represents the time span from the COVID outbreak to the recovery, and the height signifies the maximal reduction in travel. They suggested that travel behavior during the recovery period was affatced by service facilities, social context, transport supply, and individual psychological state, etc.

Existing literature has explored various aspects of public transport use during and after the pandemic, focusing on travelers' psychological resilience, perceived risks of contagion, the effects on vulnerable populations, and the pace of recovery in ridership as the pandemic evolves. Zheng et al.(2021) investigated the psychological resilience of travelers against "travel fear" during the COVID pandanmic and how to build the resilience and adoption of cautious travel behaviors during the post-COVID era. While the evidence indicates an exceptionally high level of fear related to contracting an infection among public transport users, some passengers who continued to use public transport perceived the risk of contagion to be lower than those who chose to avoid it entirely (Nelson et al., 2023). Xiao et al. (2022) studied the vulnerability and resilience of public transport ridership and measured the decline and recovery of ridership during the COVID pandemic, highlighting the importance of addressing the daily commuting needs of the vulnerable groups to prevent the pandemic from intensifying social inequality. Wang et al. (2022) examined the recovery of public transport travel after the initial wave of the pandemic and suggested that public transport use rebounded slowly due to urban factors and individual differences. The findings revealed the distinct travel behavior resilience among different SES groups, emphasizing the need for policymakers to consider these disparities in transport management. In order to examine how the psychological needs arising post-COVID-19 impact passenger satisfaction and loyalty towards bus services, Hsieh (2023) constructed a hierarchy of bus service requirements for riders across diverse SESs at different usage stages by leveraging Maslow's hierarchy of needs theory.

A comprehensive examination of the interplay between NPIs, COVID-19 vaccination, and their contributions to travel behavior resilience during the pandemic has been provided. Leung et al. (2021) highlighted the crucial role of effective vaccines with high uptake in managing the COVID-19 pandemic and recommended gradual easing of NPIs during the recovery period to reduce related hospitalizations and deaths. While NPIs are essential during the initial phases of the pandemic or in areas with low vaccination rates, vaccines offer a long-term solution for safe and sustainable travel (Doroshenko, 2021). However, the real-world impact of NPIs versus vaccination, or a combination of both, on COVID-19 remains uncertain. To address this, Ge et al. (2022) proposed a Bayesian inference model to assess the impact of NPIs and vaccination on reducing COVID-19 transmission based on a large-scale dataset in Europe. The results show that NPIs complemented vaccination to curb COVID-19 spread, with NPI relaxation influenced by vaccination rates, control targets, and vaccine efficacy against current and new variants. Wylezinski et al. (2021) found that COVID-19 vaccination rates play a crucial role in determining future COVID-19 disease risk. As vaccination rates increased, the relative importance of demographic characteristics such as age, race, and ethnicity decreased. Conversely, socio-economic and environmental factors, including access to healthcare and transportation, became more influential in determining COVID-19 risks. Mladenović et al. (2022) discussed how vaccination could be used as a resilience strategy for the tourism industry, with evidence from Serbia, emphasizing the positive impact of vaccination on the inflow of foreign tourists and the destination image and reputation of the country. Boto-García & Francisco Baños Pino (2022) investigated the relationship between COVID-19 vaccination and travel behavior and found that vaccination could increase travel propensity by lowering perceived health risks and associated travel anxieties, suggesting that vaccines can be an effective tool for the recovery of human mobility. Hu et al. (2022) indicated that vaccine hesitancy alone cannot entirely account for the observed variations in vaccination rates and suggested that public health officials should consider other factors, such as social vulnerability and urbanicity, when designing interventions to increase vaccination rates. Hu et al. (2023) analyzed differences in COVID incidence rates during the Omicron surge, examined the interplay between vaccination, human mobility, and COVID-health outcomes, studied time-varying effects and socio-economic disparities, and offered evidence and policy insights for a future pandemic, considering vaccination, NPIs, and social equality.

Overall, the key literature investigating travel behaviour changes and resilience, and , interventions of NPIs and vaccination during the COVID-19 pandemic has been summarized in Table 1.

Table 1: Key Literature investigating Travel behaviour change, interventions, and resilience during COVID-19 pandemic

Literature	Data	Travel behavior change	Interventions	diverse SES?	Investigating resilience?
Matson et al. 2023)	before-pandemic and during-pandemic surveys	ride-hailing and active modes for leisure purposes	NPI	×	×
Chinazzi et al. (2020)	airline transportation data from IATA and GLEAM simulation data	international travel	NPI	×	×
Xiong et al. (2020)	mobile device location data in the US	Out-of-county trips	NPI	✓	×
Böhmer et al. (2020)	contact tracing and interviews with confirmed COVID-19 cases	×	NPI	×	×
Tirachini& Cats (2020)	synthesis of surveys, GPS tracking, and census data	routes, departure time, mode shifts, and destinations	NPI	×	×
Beck&Hensher (2020)	survey examining household travel and activity patterns	weekly trips with different modes and purposes	NPI	×	×
Hu & Chen (2021)	20-year transit ridership in Chicago	transit ridership	NPI	✓	×
Zheng et al., 2021)	online survey	travel fear	NPI	✓	✓
Gao et al. (2020)	open source project and census data	travel distance and stay-at-home	NPI	×	×
König & Dreßler(2021)	online survey, interviews	changes in trips and mode choice	×	✓	×
Przybylowski et al. (2021)	surveys, interviews, focus groups, and observational studies	travel patterns, modes and frequency	NPI	×	×
Wang, Kaza, et al. (2022)	mobile device data from SafeGraph	changes in visits to different destinations	×	✓	✓
Xiao et al. (2022)	station check-ins data in Salt Lake County, Utah	resilience of public transport ridership	×	✓	✓
Xi et al. (2023)	mobile device location data	WFH, work/nonwork trips, out-of-county trips, travel miles	×	✓	×
Leung et al. (2021)	case study data	international travel	vaccination	×	✓
Wylezinski et al. (2021)	COVID-19 testing data, vaccination rates, and social determinants	×	vaccination	✓	×
Wang et al. (2022)	subway trip records in China	public transport use	×	✓	✓
Hu et al. (2023)	US county-level COVID-19 data	human mobility	vaccination	✓	×
Hu et al. (2022)	the American Community Survey, and mobile device data	human mobility trends	vaccination & NPI	✓	×
Hsieh (2023)	questionnaire survey	hierarchy of bus needs	×	✓	✓

2.3 Our contributions

The existing literature has studied various travel behavior changes, the impact of interventions such as NPIs and vaccination on the resilience of travel behavior, and the disparities of mobility response across diverse SESs (see Table 1). However, few studies have investigated the impact of vaccination intervention on travel behavior resilience in the context of Metropolitan, Micropolitan, and Rural areas. Until now, no study has inferred the causal impact of the vaccination intervention on different types of travel behavior and compared the distinct human mobility response to vaccination rates, epidemiological indicators, and weather conditions across these contrasting types of areas during the recovery period of pandemic. This study aims to fill in these research gaps and propose a joint framework that incorporates Bayesian structural time series (BSTS) model and partial least regression squares (PLSR) model, using an integrated county-level dataset comprising mobile device location data with over 150 million active samples, vaccination rates, COVID-19 epidemiological indicators, and weather data in the US from 01/01/2020 to 20/04/2021. The proposed framework can infer the relative impact of the vaccination intervention on the recovery of different travel behaviors (i.e., WFH%, work/nonwork trips, out-of-county trips%, and travel miles) and estimate the diverse human mobility response to COVID vaccination rates, epidemiological indicators, and weather conditions. The modelling results provide evidence-based insights into understanding how vaccination intervention can impact the travel behavior resilience and the interrelationship between travel behavior and epidemiological indicators, vaccination rates, as well as weather conditions, to identify the disparities of the travel behavior resilience by such interventions across diverse areas. Furthermore, the findings can facilitate policymakers understand the travel behavior resilience across diverse areas, inform decision-making, equitable planning, and the development of sustainable and resilient transportation systems that can adapt to future pandemics.

3. Research framework and methodology

This section introduces the dataset used in this study (Section 3.1), research framework (Section 3.2), Bayesian time series structural model (Section 3.3), and Partial least squares regression model (Section 3.4).

3.1 Data description

We use an integrated and processed dataset in the US obtained from multiple third-party data providers, including over 150 million monthly active mobile device samples from the University of Maryland COVID-19 Impact Analysis Platform (Maryland Transportation Institute, 2020), the county-level vaccination rates data from Centers for Disease Control and Prevention (CDC)[3], COVID-19 epidemiological indicators (e.g. COVID-19 incidence rate, death rate, testing rate) from Johns Hopkins Coronavirus Resource Center[4]), and the weather data from Visual Crossing Weather API[5]. The daily travel data, such as WFH%, work/nonwork trips, out-of-county trips%, and travel miles, were aggregated at the county-level from 1 January 2020 to 20 April 2021, wherein the 1300 US counties are divided into three categories based on the US rural-urban commuting area codes (RUCA)[6]: Metropolitan areas (686 counties), Micropolitan areas (158 counties), and Rural areas (456 counties).

Table 2 summarizes the US county-level descriptive statistics for the variables in the data set, which will be used in the BSTS and PLSR models later. Note that the actual county-level time series data of WFH%, work trips, nonwork trips, out-of-county trips%, and travel miles, are visualized in the second subfigure of Figure 2, Figure 5, Figure 8, Figure 11, Figure 14, respectively.

To fully capture all covariates, county attributes, public health measures, are integrated with other information into the data source. The data processing includes the following steps: 1) a heuristic rule-based methodology is employed to identify activity locations and integrated with Point-of-Interest (POI) information; 2) a rule-based recursive algorithm is used to identify trips from raw location points; 3) a multi-level weighting procedure expands the observed trips to the entire US population, using device-level and trip-level weights to ensure data representativeness in the total population; 4) various human mobility metrics are calculated via a post-processing step based on the weighted trip roster (Xiong et al., 2020). In order to identify and merge

[3] County-level COVID-19 Vaccinations in the United States
[4] Johns Hopkins Coronavirus Resource Center
[5] Visual Crossing Weather API
[6] The rural-urban commuting area (RUCA) codes classify US census tracts using measures of population density, urbanization, and daily commuting. The classification contains two levels. Whole numbers (1–10) delineate metropolitan (1-3), micropolitan (4-6), small towns and rural areas (7-10) based on the size and direction of the primary (largest) commuting flows.

duplicate device observations, remove outliers, and check on data consistency issues (e.g., devices with unreasonably high-speed readings), a state-of-the-practice procedure for mobile device location data cleaning and quality control was conducted by the research team (Zhang et al., 2020) based on the four dimensions of data quality assessment: consistency, accuracy, completeness, and timeliness.

Table 2: Descriptive statistics of the variables

		Metropolitan Areas				Micropolitan Areas				Rural Areas			
		Mean	Std.	Min.	Max.	Mean	Std.	Min.	Max.	Mean	Std.	Min.	Max.
Travel behavior	WFH%	27.4	11.5	2.3	49.4	27.8	11.5	2.3	2.3	26.9	11.4	2.3	47
	Work trips	0.5	0.2	0	4.9	0.5	0.2	0	5.8	0.5	0.2	0	1.3
	Nonwork trips	3.1	0.9	0	73.2	3.1	0.7	0	34.3	3.1	0.6	1.2	7.4
	Out-of-county trips %	33.9	12.5	0	100	34.8	12.03	0	100	35.7	10.5	12.2	75.8
	Travel Miles	49.9	23.9	0	299.7	48.1	20.6	0	299.9	46.8	15.3	8.7	293.2
Vaccination	Vaccination rate	2.2	6.5	0	60.60	2.2	6.6	0	64.5	2.1	6.1	0	41
Epidemiological indicators	Covid incidence rate	30.6	311.8	0	28408	21.3	112.6	0	14871	9.1	19.5	0	424
	Covid death rate	11.1	12.2	0	83.97	11.3	11.3	0	83.9	11.4	12.1	0	84
	Covid test rate	374.7	437.8	0	2348.2	363.8	421.4	0	2437.7	310.6	350.8	0	2031.3
Weather conditions	Temp (°)	10.6	10.4	-40.1	35.70	11.5	10.3	-45.6	46.1	11.9	10.0	-27.3	32.3
	IsRain (0,1)	0.4	0.5	0	1	0.31	0.46	0	1	0.39	0.5	0	1
	IsSnow (0,1)	0.08	0.3	0	1	0.06	0.25	0	1	0.1	0.3	0	1

Note. *WFH%* denotes the percentage of workforce working from home calculated by MTI based on changes in work trips and unemployment claims. *Work trips* denotes the number of work trips per person per day and is defined as going to or coming home from work location. *Nonwork trips* denotes the number of non-work trips per person per day for diverse trip purposes (grocery, park, restaurant, etc). *Out-of-county trips %* denotes the percentage of all trips that cross county borders calculated by MTI. *Travel Miles* denotes the average person-miles travelled on all modes (car, train, bus, plane, bike, walk, etc.) per person per day. *Covid incidence rate* denotes the number of COVID-19 daily new cases per 1000 people per day. *Vaccination rate* denotes the percent of population with at least one dose based on the jurisdiction and county where COVID-19 vaccine recipient lives. *Covid death rate* denotes the percentage of deaths among all COVID-19 cases. *Covid test rate* denotes the number of COVID-19 tests completed per 1000 people. *Temp (°)* denotes the average daily temperature. *IsRain* is a dummy variable indicates whether it is rainy (1) or not (0) per day. *IsSnow* is a dummy variable indicates whether it is snowy (1) or not (0) per day.

3.2 Research framework

The United States adopted a phased approach to its COVID-19 vaccination program, and certain groups were prioritized based on risk factors such as age, underlying health conditions, and occupational exposure. According to the county-level vaccination rates data obtained from CDC[2], by 16/01/2021, the vaccination campaign had progressed to the extent that all counties in the dataset had begun their vaccination schemes. From this date forward, there was a consistent intervention across all 1300 counties in the dataset, marking it as a crucial point for analysis. Therefore, we select 16/01/2021 as the vaccination intervention date, and the county-level time series data can be divided into the pre-intervention period (i.e., from 01/01/2020 to 15/01/2021) and the post-intervention period (i.e., from 16/01/2021 to 20/04/2021).

We propose an analytical framework by incorporating time-series prediction, causal impact inferring, and regression modeling (see Figure 1). Within the research framework, we first build BSTS models to infer the relative impact of vaccination intervention on five types of travel behaviors (WFH%, work/nonwork trips, out-of-county trips, travel miles) across Metropolitan, Micropolitan, and Rural areas, considering the impact of COVID epidemiological indicators and weather conditions. BSTS models allow for the estimation of causal impact of vaccination by comparing actual travel behavior data to the predicated results in counterfactual scenarios (i.e., without the implementation of vaccination). After inferring the relative impact of vaccination on travel behaviors and initially identifying the most influential covariates that affect travel behavior resilience through BSRS models, we proceed to develop PLSR models and accurately estimate how these independent variables (i.e., COVID epidemiological indicators, weather conditions, and vaccination rates) would impact travel behaviors across Metropolitan, Micropolitan, and Rural areas during the recovery period of the pandemic (Jan-April 2021). Note that except for the covariates in BSTS model, we integrate COVID vaccination rates as another independent variable in the PLSR models.

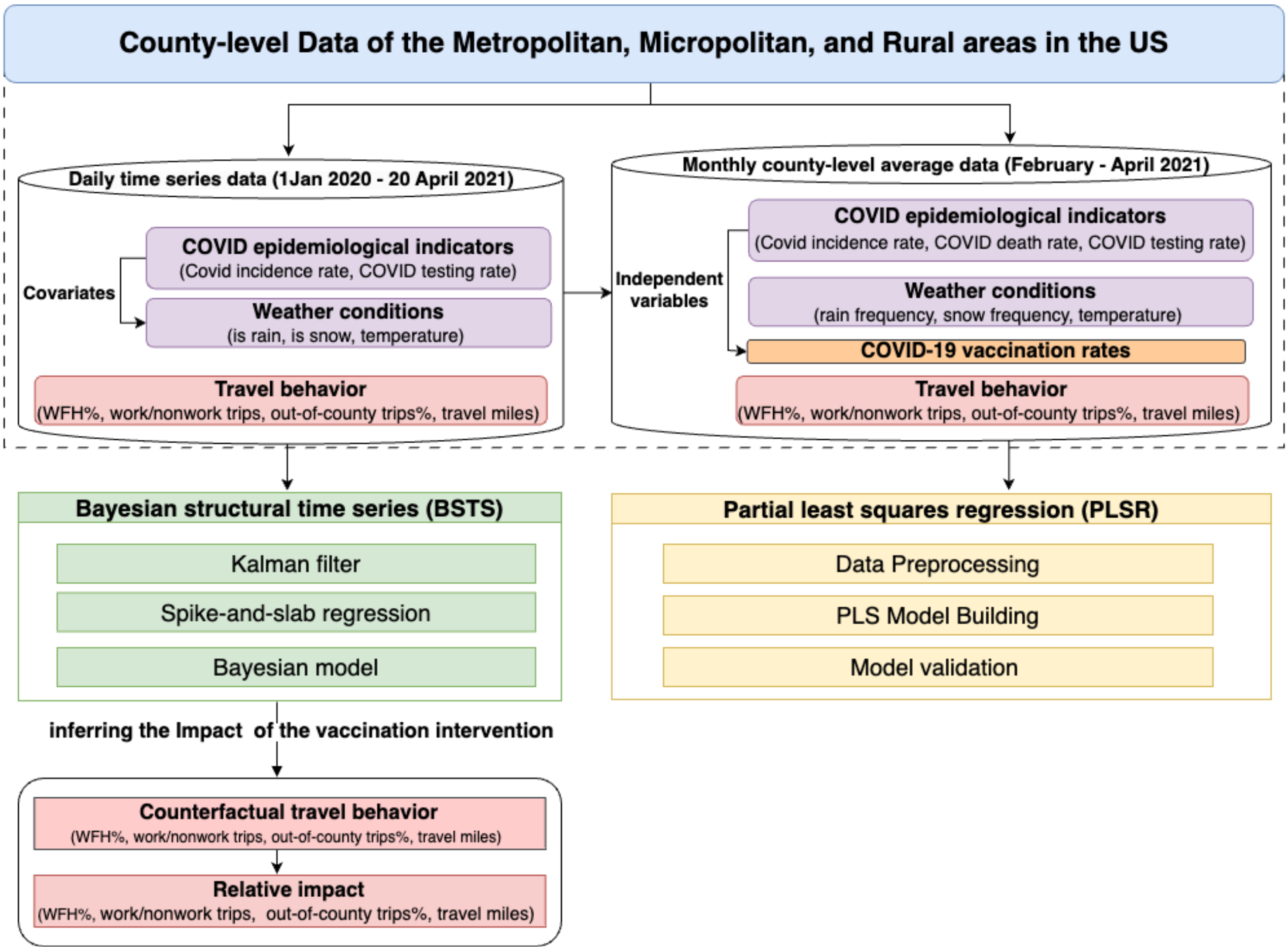


Figure 1.Research Framework

3.3 Bayesian structural time-series model

The BSTS model integrates feature selection with time-series forecasting and was first introduced as a tool to demonstrate the potential of Google search data in enhancing near-term economic time-series nowcasts (Scott & Varian, 2014, 2015). The BSTS model is underpinned by three main components: 1) the utilization of Kalman filtering for discerning trends and seasonality in time series, 2) the application of "spike-and-slab" regression for efficient variable selection, and 3) the employment of Bayesian model averaging to select the most accurate models for the eventual prediction. The BSTS model is articulated by two fundamental equations (Brodersen et al., 2015): the observation equation (Eq. (1)) and the state equation (Eq. (2)).

$$\boldsymbol{Y}_t = \boldsymbol{Z}_t^T \boldsymbol{\alpha}_t + \boldsymbol{\varepsilon}_t, \qquad \boldsymbol{\varepsilon}_t \sim N(0, \boldsymbol{\sigma}_t^2), \tag{1}$$

$$\boldsymbol{\alpha}_{t+1} = \boldsymbol{T}_t \boldsymbol{\alpha}_t + \boldsymbol{R}_t \boldsymbol{\eta}_t, \qquad \boldsymbol{\eta}_t \sim N(0, \boldsymbol{\omega}_t^2), \tag{2}$$

where $\boldsymbol{Y}_t = [WFH_t, WT_t, NWT_t, OC_t, M_t]$, WFH_t is the observed daily county-level incidence of WFH per person, WT_t is the daily county-level work trips per person, NWT_t is the daily county-level nonwork trips per person, OC_t is the daily county-level out-of-county trips% per person, and M_t is the daily county-level travel miles per person. $\boldsymbol{\alpha}_t = [\alpha_t^{WFH}, \alpha_t^{WT}, \alpha_t^{NWT}, \alpha_t^{OC}, \alpha_t^{M}]$ denotes the state vector of latent variables, while $\boldsymbol{Z}_t^T = [Z_t^{WFH}, Z_t^{WT}, Z_t^{NWT}, Z_t^{OC}, Z_t^{M}]$ is a connecting vector between the observed and the latent variables. The matrix $\boldsymbol{T}_t = [T_t^{WFH}, T_t^{WT}, T_t^{NWT}, T_t^{OC}, T_t^{M}]$ describes how the state vector $\boldsymbol{\alpha}_t = [\alpha_t^{WFH}, \alpha_t^{WT}, \alpha_t^{NWT}, \alpha_t^{OC}, \alpha_t^{M}]$ evolves over time. The errors $\boldsymbol{\varepsilon}_t = [\varepsilon_t^{WFH}, \varepsilon_t^{WT}, \varepsilon_t^{NWT}, \varepsilon_t^{OC}, \varepsilon_t^{M}]$ and $\boldsymbol{\eta}_t = [\eta_t^{WFH}, \eta_t^{WT}, \eta_t^{NWT}, \eta_t^{OC}, \eta_t^{M}]$ represent the observation and system errors, which are independent and obey Gaussian distributions with noise variances $\boldsymbol{\sigma}_t = [\sigma_t^{WFH}, \sigma_t^{WT}, \sigma_t^{NWT}, \sigma_t^{OC}, \sigma_t^{M}]$ for observation errors and $\boldsymbol{\omega}_t = [\omega_t^{WFH}, \omega_t^{WT}, \omega_t^{NWT}, \omega_t^{OC}, \omega_t^{M}]$ for system errors. The control matrix $\boldsymbol{R}_t = [R_t^{WFH}, R_t^{WT}, R_t^{NWT}, R_t^{OC}, R_t^{M}]$ facilitates the integration of various state components.

The Kalman filter is particularly useful for estimating these components in a state-space representation where the state vector includes the level, trend, and seasonal effects, and error terms. The recursive nature of the Kalman filter allows it to efficiently handle large time series datasets and update estimates in real-time. One of the significant benefits of the BSTS model is its modular nature, capturing seasonal changes, accounting for regression effects, and integrating other pivotal components. This research incorporates the semi-local linear trend (Eq. (3) - Eq. (4)), the weekly seasonality (Eq. (5)), the monthly annual seasonality (Eq. (6)), and contemporaneous covariates with coefficients (Eq. (7)) (Scott & Varian, 2015).

$$\boldsymbol{\mu}_{t+1} = \boldsymbol{\mu}_t + \boldsymbol{\delta}_t + \boldsymbol{\eta}_{\mu,t}, \qquad \boldsymbol{\eta}_{\mu,t} \sim N\left(0, \boldsymbol{\sigma}_{\mu}^2\right), \tag{3}$$

$$\boldsymbol{\delta}_{t+1} = \boldsymbol{L} + \boldsymbol{\rho}(\boldsymbol{\delta}_t - \boldsymbol{L}) + \boldsymbol{\eta}_{\delta,t}, \qquad \boldsymbol{\eta}_{\delta,t} \sim N\left(0, \boldsymbol{\sigma}_{\delta}^2\right), |\boldsymbol{\rho}| < 1, \tag{4}$$

$$\boldsymbol{w}_{t+1,1} = -\sum_{s=2}^{S} \boldsymbol{\gamma}_{t,s} + \boldsymbol{\eta}_{w,t}, \qquad \boldsymbol{\eta}_{w,t} \sim N(0, \boldsymbol{\sigma}_{w}^2), \tag{5}$$

$$\boldsymbol{m}_{t+1,1} = -\sum_{s=2}^{S} \boldsymbol{\gamma}'_{t,s} + \boldsymbol{\eta}_{m,t}, \qquad \boldsymbol{\eta}_{m,t} \sim N(0, \boldsymbol{\sigma}_{m}^2), \tag{6}$$

$$\boldsymbol{Z}_t^T = \boldsymbol{\beta}^T \mathbf{x}_t \tag{7}$$

where $\boldsymbol{\mu}_t = [\mu_t^{WFH}, \mu_t^{WT}, \mu_t^{NWT}, \mu_t^{OC}, \mu_t^{M}]$ represents the trend at time t; $\boldsymbol{\delta}_t = [\delta_t^{WFH}, \delta_t^{WT}, \delta_t^{NWT}, \delta_t^{OC}, \delta_t^{M}]$ is the slope at time t and shows autoregressive variation around a long-term slope, denoted as $\boldsymbol{L} = [L_t^{WFH}, L_t^{WT}, L_t^{NWT}, L_t^{OC}, L_t^{M}]$; $\boldsymbol{\rho} = [\rho_t^{WFH}, \rho_t^{WT}, \rho_t^{NWT}, \rho_t^{OC}, \rho_t^{M}]$ is the learning rate, determining the pace at which the local trend updates. Here S denotes the number of weeks from 01/01/2020 to 20/04/2021, namely, S=67. $\boldsymbol{w}_{t+1,1} = [w_{t+1,1}^{WFH}, w_{t+1,1}^{WT}, w_{t+1,1}^{NWT}, w_{t+1,1}^{OC}, w_{t+1,1}^{M}]$ and $\boldsymbol{m}_{t+1,1} = [m_{t+1,1}^{WFH}, m_{t+1,1}^{WT}, m_{t+1,1}^{NWT}, m_{t+1,1}^{OC}, m_{t+1,1}^{M}]$ respectively indicate the primary elements of the weekly and monthly state vectors for the forthcoming time step. $\boldsymbol{\beta}$= $[\beta_{t+1,1}^{WFH}, \beta_{t+1,1}^{WT}, \beta_{t+1,1}^{NWT}, \beta_{t+1,1}^{OC}, \beta_{t+1,1}^{M}]$ is the vector of regression coefficients; $\mathbf{x}_t$ is the vector of contemporaneous covariates, i.e., $\mathbf{x}_t = [CR_t, CT_t, Temp_t, IsRain_t, IsSnow_t]$, where CR_t denotes the COVID incidence rate, CT_t denotes the COVID testing rate, $Temp_t$ denotes the temperature, $IsRain_t$ denotes whether rain or not, and $IsSnow_t$ denotes whether snow or not at time t. The terms $\boldsymbol{\eta}_{\mu,t} = [\eta_{\mu,t}^{WFH}, \eta_{\mu,t}^{WT}, \eta_{\mu,t}^{NWT}, \eta_{\mu,t}^{OC}, \eta_{\mu,t}^{M}]$, $\boldsymbol{\eta}_{\delta,t} = [\eta_{\delta,t}^{WFH}, \eta_{\delta,t}^{WT}, \eta_{\delta,t}^{NWT}, \eta_{\delta,t}^{OC}, \eta_{\delta,t}^{M}]$, are the independent error components that follow a Gaussian distribution; each is characterized by its corresponding noise variance, namely, $\boldsymbol{\sigma}_{\mu} = \left[\sigma_{\mu}^{WFH}, \sigma_{\mu}^{WT}, \sigma_{\mu}^{NWT}, \sigma_{\mu}^{OC}, \sigma_{\mu}^{M}\right]$, $\boldsymbol{\sigma}_{\delta} = \left[\sigma_{\delta}^{WFH}, \sigma_{\delta}^{WT}, \sigma_{\delta}^{NWT}, \sigma_{\delta}^{OC}, \sigma_{\delta}^{M}\right]$, $\boldsymbol{\sigma}_{w} = [\sigma_{w}^{WFH}, \sigma_{w}^{WT}, \sigma_{w}^{NWT}, \sigma_{w}^{OC}, \sigma_{w}^{M}]$, and $\boldsymbol{\sigma}_{m} = [\sigma_{m}^{WFH}, \sigma_{m}^{WT}, \sigma_{m}^{NWT}, \sigma_{m}^{OC}, \sigma_{m}^{M}]$. The "spike-and-slab" regression, integral to the BSTS model, facilitates effective feature selection (Scott & Varian, 2015). In this context, the term "spike" refers to the likelihood of a specific coefficient being zero, whereas "slab" denotes the prior distribution assigned to the regression coefficients. This spike-and-slab prior can be written as Eq. (8):

$$p(\vartheta, \beta, \sigma_{\varepsilon}^{-2}) = p(\vartheta) p(\sigma_{\varepsilon}^{2} | \vartheta) p(\beta_{\vartheta} | \vartheta, \sigma_{\varepsilon}^{2}) \tag{8}$$

where ϑ is a vector indicating the inclusion of an intervention or regressor that represents the implementation of vaccination scheme in this study, the regressor is a binary variable (0/1) which is 0 before the intervention and 1 after the intervention, namely, $\vartheta_i = 1$ if $\beta_i \neq 0$ and $\vartheta_i = 0$ if $\beta_i = 0$, and the vector β_{ϑ} includes the nonzero coefficients. Meanwhile, σ_{ε}^2 represents the residual variance of the regression model. Note that an advantageous way to define the prior distribution is to assume that the "spike" component $p(\vartheta)$ adheres to a Bernoulli distribution, while the "slab" component $p(\beta_{\vartheta} | \vartheta, \sigma_{\varepsilon}^2)$ follows a conjugate normal-inverse Gamma distribution. Such a prior configuration serves as an effective default but retains the adaptability to accommodate more specific prior information when necessary (Scott & Varian, 2014, 2015).

After fitting the BSTS models, forecasting the time series into the future without the intervention will give us a "counterfactual" scenario, which is essentially what we would expect to have happened in the absence of the intervention. Utilizing BSTS to discern impact can be distilled into three primary phases (Brodersen et al., 2015):

1) **Parameter and State Vector Determination:** Initially, we conduct posterior simulation based on pre-intervention data, i.e., $WFH_{1:j}$, $WT_{1:j}$, $NWT_{1:j}$, $OC_{1:j}$, $M_{1:j}$, to obtain model parameters and state vectors.

2) **Counterfactual Prediction:** The next step is to predict the counterfactual posterior distribution, i.e., $p\left(\underset{j+1:n}{WFH} \mid WFH_{j+1:n}, \mathbf{x}_{j+1:n}\right)$, $p\left(\underset{j+1:n}{WT} \mid WT_{j+1:n}, \mathbf{x}_{j+1:n}\right)$, $p\left(\underset{j+1:n}{NWT} \mid NWT_{j+1:n}, \mathbf{x}_{j+1:n}\right)$, $p\left(\underset{j+1:n}{OC} \mid OC_{j+1:n}, \mathbf{x}_{j+1:n}\right)$, $p\left(\underset{j+1:n}{M} \mid M_{j+1:n}, \mathbf{x}_{j+1:n}\right)$, during the intervention period, leveraging the model fine-tuned in $j+1\colon n$ steps.

3) **Calculate the impact:** We compare the actual observed travel behavior data (with the intervention) to the counterfactual forecast (without the intervention) to measure the impact of the vaccination intervention, respectively. We compute the posterior distribution of pointwise impact, the pointwise relative impact, and the average relative impact (shortened as "relative impact") of the incidence of WFH (Eq. (9)), work trips (Eq. (10)), nonwork trips (Eq. (11)), out-of-county trips (Eq. (12)), and travel miles (Eq. (13)).

$$\phi_t^{WFH(k)} := WFH_t - WFH_t^{(k)},\ \ \ddot{\phi}_t^{WFH(k)} = \phi_t^{WFH(k)}/WFH_t^{(k)},\ \ \bar{\phi}_{j+1:n}^{WFH(k)} = \frac{1}{n-j}\sum_{t=j+1}^{n}\ddot{\phi}_t^{WFH(k)} \tag{9}$$

$$\phi_t^{WT(k)} := WT_t - WT_t^{(k)},\ \ \ddot{\phi}_t^{WT(k)} = \phi_t^{WT(k)}/WT_t^{(k)},\ \ \bar{\phi}_{j+1:n}^{WT(k)} = \frac{1}{n-j}\sum_{t=j+1}^{n}\ddot{\phi}_t^{WT(k)} \tag{10}$$

$$\phi_t^{NWT(k)} := NWT_t - NWT_t^{(k)},\ \ \ddot{\phi}_t^{NWT(k)} = \phi_t^{NWT(k)}/NWT_t^{(k)},\ \ \bar{\phi}_{j+1:n}^{NWT(k)} = \frac{1}{n-j}\sum_{t=j+1}^{n}\ddot{\phi}_t^{NWT(k)} \tag{11}$$

$$\phi_t^{OCT(k)} := OCT_t - OCT_t^{(k)},\ \ \ddot{\phi}_t^{OCT(k)} = \phi_t^{OCT(k)}/WFH_t^{(k)},\ \ \bar{\phi}_{j+1:n}^{OCT(k)} = \frac{1}{n-j}\sum_{t=j+1}^{n}\ddot{\phi}_t^{OCT(k)} \tag{12}$$

$$\phi_t^{M(k)} := M_t - M_t^{(k)},\ \ \ddot{\phi}_t^{M(k)} = \phi_t^{M(k)}/M_t^{(k)},\ \ \bar{\phi}_{j+1:n}^{M(k)} = \frac{1}{n-j}\sum_{t=j+1}^{n}\ddot{\phi}_t^{M(k)} \tag{13}$$

where k is the draw of a state; WFH_t, WT_t, NWT_t, OCT_t, and M_t respectively denote the observed daily WFH%, work trips, nonwork trips, out-of-county trips%, and travel miles, while $WFH_t^{(k)}$, $WT_t^{(k)}$, $NWT_t^{(k)}$, $OCT_t^{(k)}$, and M_t respectively denote the predicted daily WFH%, work trips, nonwork trips, out-of-county trips%, and travel miles at the draw k. $\phi_t^{WFH(k)}$, $\phi_t^{WT(k)}$, $\phi_t^{NWT(k)}$, $\phi_t^{OCT(k)}$, $\phi_t^{M(k)}$ respectively denote the approximate posterior predictive density of the pointwise impact on WFH%, work trips, nonwork trips, out-of-county trips%, and travel miles, attributed to the intervention of vaccination implementation at t; $\ddot{\phi}_t^{WFH(k)}$, $\ddot{\phi}_t^{WT(k)}$, $\ddot{\phi}_t^{NWT(k)}$, $\ddot{\phi}_t^{OCT(k)}$, $\ddot{\phi}_t^{M(k)}$ respectively denote the corresponding density of the pointwise relative impact on WFH%, work trips, nonwork trips, out-of-county trips%, and travel miles, attributed to the intervention of vaccination implementation at t; $\bar{\phi}_{j+1:n}^{WFH(k)}$, $\bar{\phi}_{j+1:n}^{WT(k)}$, $\bar{\phi}_{j+1:n}^{NWT(k)}$, $\bar{\phi}_{j+1:n}^{OCT(k)}$, $\bar{\phi}_{j+1:n}^{M(k)}$ respectively denote the posterior running average impact following the intervention of vaccination; In this research, j is set as 16/01/2021 which is the intervention date when all of the US counties in the dataset started the vaccination scheme, and n is set as 20/04/2021 which is the end date of observation.

The BSTS model can provide nuanced insights into the evolving impacts over time, making it indispensable for examining the dynamic effects of vaccination on travel behavior, and is particularly adept at navigating the shifting effects of current covariates such as weather conditions and COVID epidemiological indicators, guaranteeing a more precise evaluation of the influence exerted by the vaccination schemes.

3.4 Partial least squares regression model

We next estimate the impact of epidemiological indicators, as well as weather conditions on travel behavior across Metropolitan, Micropolitan and Rural areas. Since vaccination rates, Covid incidence rates, Covid death rates, and COVID testing rates, are inherently intercorrelated, given the intertwined nature of disease spread, its control measures, and their consequences, using traditional regression methods can pose challenges in such settings due to multicollinearity. Therefore, we employ partial least squares regression (PLSR) modelling, which fits a linear regression by decomposing both the dependent and independent variables into orthogonal scores and loadings and then determines the regression coefficients using these scores. After this process, PLSR translates the coefficients back into the context of the initial variables. PLSR allows for robust analysis, capturing the most influential patterns within vaccination rates, epidemiological indicators, and weather conditions, and effectively mapping them to different travel behaviors (de Jong, 1993).

$$\boldsymbol{X} = \boldsymbol{A}\boldsymbol{P}^{\boldsymbol{T}} + \boldsymbol{E} \tag{14}$$

$$\boldsymbol{Y} = \boldsymbol{U}\boldsymbol{Q}^{\boldsymbol{T}} + \boldsymbol{F} \tag{15}$$

$$\boldsymbol{Y} = \boldsymbol{X}\boldsymbol{K}^{\boldsymbol{T}} + \boldsymbol{\Theta} \tag{16}$$

where $\boldsymbol{X}$ represents the matrix of independent variables. This matrix incorporates the average monthly values for various epidemiological indicators (i.e., COVID incidence rates, vaccination rates, and death rates) as well as weather factors (i.e., temperature and occurrences of rain or snow) for the period of February to April 2021, aligning with the rollout of the vaccination scheme. $\boldsymbol{Y}$ is the matrix of dependent variables, capturing the mean monthly values at the county level for diverse travel behaviors: WFH%, work trips, nonwork trips, out-of-county trips%, and travel miles during that same three-month span. $\boldsymbol{K}$ represents the coefficient matrix. $\boldsymbol{A}$ and $\boldsymbol{U}$ are denote the orthogonal scores for $\boldsymbol{X}$ and $\boldsymbol{Y}$, respectively, while $\boldsymbol{P}$ and $\boldsymbol{Q}$ represent their corresponding orthogonal loadings. $\boldsymbol{E}$, $\boldsymbol{F}$, $\boldsymbol{\Theta}$ are the independent and identically distributed error terms in the model. With each iteration during the decomposition process (Eq. (14)-(16)), the data matrices ($\boldsymbol{X}$ and $\boldsymbol{Y}$) are deflated and the fitted components are subtracted, producing new data matrices where $\boldsymbol{E}$ and $\boldsymbol{F}$ replace $\boldsymbol{X}$ and $\boldsymbol{Y}$ in subsequent iterations. The optimal number of iterations is determined by the cross-validated root mean squared error of prediction (RMSEP) (Wehrens & Mevik, 2007). In this research, we compute P-values for coefficients using Jack-Knifing resampling combined with 10-fold cross-validation. The perturbed model coefficients obtained through cross-validation are compared with those obtained from the full dataset, providing insights into model stability, overfitting, and the potential need for model adjustments (Martens & Martens, 2000).

4. Results analysis

This section analyzes results of BSTS models (Section 4.1) and PLSR models (Section 4.2).

4.1 Results of BSTS models

For each US county in the dataset, a BSTS is fitted using five types of time-series travel behavior data (i.e., WFH%, work trips, nonwork trips, out-of-county trips%, and travel miles) before the vaccination intervention (i.e., from 01/01/2020 to 15/01/2021) as the training data. We then perform cross-validation on the pre-intervention data (i.e., from 01/01/2020 to 15/01/2021) to test the robustness of the proposed BSTS model, using a rolling-window approach. We split the pre-intervention data into training set (i.e., from 01/01/2020 to 01/11/2020) and testing sets (i.e., from 02/11/2020 to 15/01/2021). For each county, we develop a BSTS model to predict the next 10 data points from the start of the testing set and compare these forecasts with the actual values in the test data to compute the Mean Absolute Percentage Error (MAPE) for this set of predictions. We expand the training data to include the 10 data points and move the prediction window one step forward in the test data to refit the BSTS model and generate new forecasts. We continue the process of expanding the training data and shifting the prediction window forward until all points in the test set have been predicted. We compute the MAPE value for each set of predictions, corresponding to a unique rolling-window iteration. The BSTS models present a reasonable goodness-of-fit in modelling WFH% (MAPE:17.64% (6.24% - 32.44%)), work trips (MAPE:18.76% (5.65% - 33.15%)), nonwork trips (MAPE: 17.89 (6.98% - 35.22%)), out-of-county trips% (MAPE: 14.66% (5.75% to 29.42%)), travel miles (MAPE: 16.54% (6.84% to 28.87%)) across 1300 US counties in the dataset.

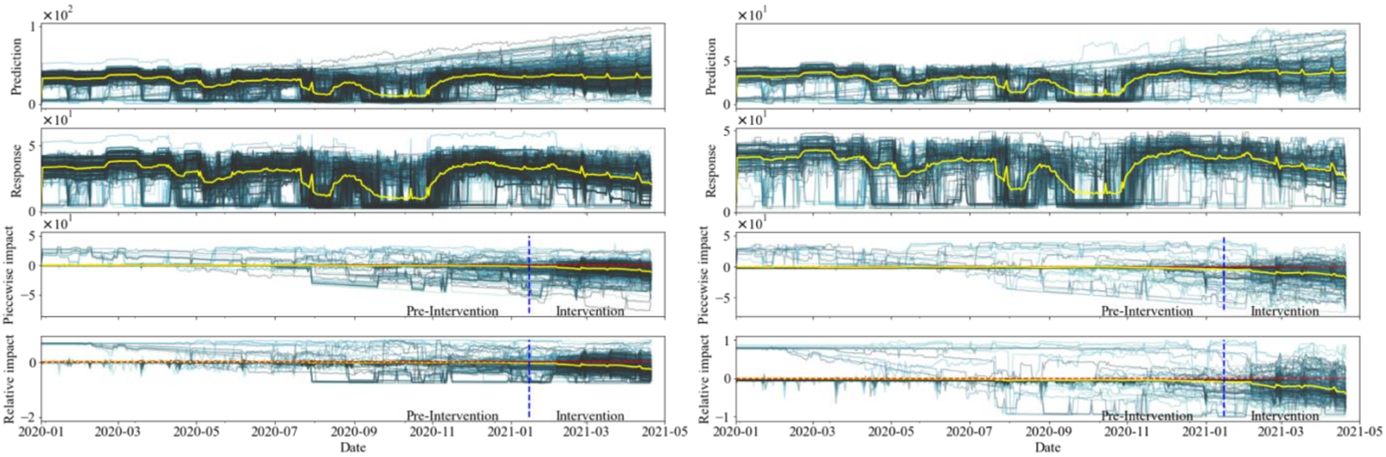
The contemporaneous covariates (i.e., COVID incidence rates, death rates, testing rates, temperature, rain/snow or not) present high posterior inclusion probabilities across five types of travel behaviors, indicating that these covariates can provide strong evidence in supporting the relevance of this covariate in explaining theses travel behavior variables. Specifically, a higher COVID testing rate (mean coefficient: -0.023) discourages WFH%, whereas other covariates boost it. Work/nonwork trips are hindered by the COVID death rates (mean coefficients: -0.081/ -0.072) and rain frequency (mean coefficient: -0.032/-0.42). Out-of-county trips% are deterred by several factors: COVID incidence rates (mean coefficient: -0.021), COVID testing rates (mean coefficient: -0.031), and rain (mean coefficient: -0.014). Travel miles have a negative impact on the COVID incidence rates (mean coefficient: -0.17), testing rates (mean coefficient: -0.51), and rain (mean coefficient: -0.079). Other covariates counteract with these effects, promoting different travel behavior. These observations offer preliminary insights into how epidemiological indicators and weather conditions influence diverse travel behavior. To measure the magnitude and significance of the vaccination rates, epidemiological indicators, and weather on travel behavior, we develop PLSR models and discuss the results in Section 4.2.

We infer the causal impact of vaccination intervention on five types of travel behavior resilience (WFH%, work/nonwork trips, out-of-county trips% and travel miles), by creating a counterfactual scenario to predict travel behavior in the absence of vaccination. After comparing the post-intervention data with the counterfactual data, we measure the relative impact attributed to the intervention of the vaccination.

BSTS modelling shows a strong capability in capturing time-series features with a promising model performance. Figure 2, Figure 5, Figure 8, Figure 11, and Figure 14 respectively visualizes the calculation process of the relative impact of vaccination intervention on five types of travel behavior resilience (WFH%, work trips, nonwork trips, out-of-county trips%, and travel miles) across Metropolitan, Micropolitan and Rural areas. Each thin line represents an individual county in an area, while the bold line represents the mean daily impact of each type of area. We predict the daily travel behavior during the post-intervention period for each county in three areas (the first subfigures of Figure 2, Figure 5, Figure 8, Figure 11, and Figure 14) based on the pre-intervention data. We subtract this prediction from the observed actual travel behavior (the second subfigures of Figure 2, Figure 5, Figure 8, Figure 11, and Figure 14) to yield an estimate of the piecewise impact (the third subfigures of Figure 2, Figure 5, Figure 8, Figure 11, and Figure 14) regarding the impact of vaccination on travel behavior. We divide the piecewise effect by the prediction to yield the relative impact (the fourth subfigures of Figure 2, Figure 5, Figure 8, Figure 11, and Figure 14). The average relative impact can be interpreted as the percentage of the decrease/increase in each travel behavior, caused by the intervention of vaccination. The significance of the impact can be obtained by calculating the Bayesian posterior one-tail-area probability (Brodersen et al., 2015), and low posterior tail-area probability indicates that the probability of obtaining such an effect by chance is small. A significant impact of vaccination on WFH% was observed during the post-intervention period (i.e., the posterior probability is less than 0.1) across 90% of counties. For example, the mean posterior probability of WFH% in the Metropolitan area is 0.063, indicating that there is a 6.3% chance of observing the effect if there were no actual effect (i.e., under the null hypothesis), and these counties where the posterior probability is greater than 10% were excluded as outliers in the PLSR models.

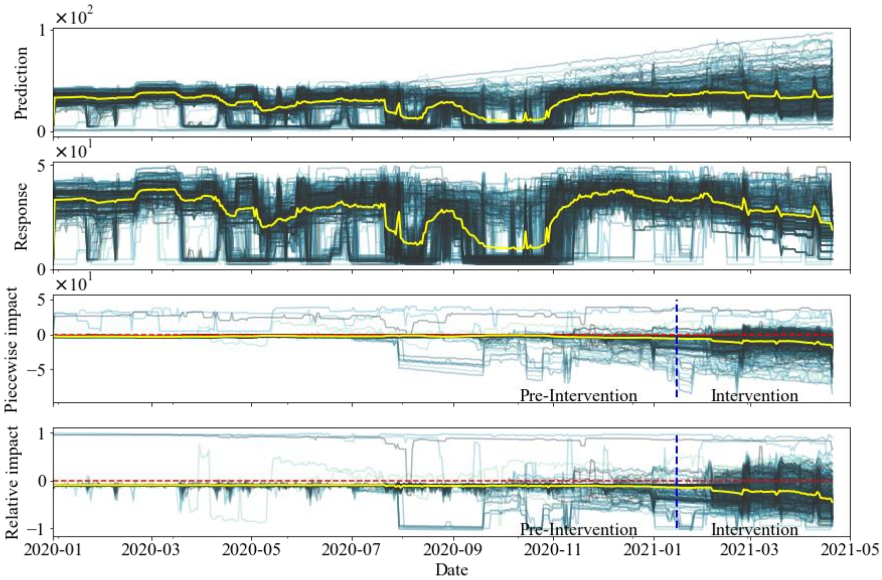
4.1.1 Inferential analysis on WFH

During the pre-intervention period, the average actual response of WFH% stood at 27.38%, 27.86%, and 27.40% for Metropolitan, Micropolitan, and Rural areas, respectively. During the post-intervention period, the average actual response of WFH% were 27.69%, 29.12%, and 28.05% for these areas. In Metropolitan areas, an initial surge in WFH% was observed, averaging at 27.44% prior to the broad vaccination initiatives. This trend displayed resilience, with only a minimal decline to 27.16% following the vaccination intervention. Micropolitan areas showed a similar trend of resilience in WFH%, starting at 27.67% before vaccination and showing a slight increase to 27.70% thereafter, suggesting a sustained adoption of remote work. Notably, Rural and Micropolitan areas exhibited the highest surge in WFH%. In contrast, WFH% in Metropolitan areas had a slight increase after vaccination, but it remained relatively close to the pre-vaccination levels (Figure 2).



(a) WFH% in Metropolitan areas

(b) WFH% in Micropolitan areas



(c) WFH% in Rural areas

Figure 2. County-level impact of vaccination implementation on WFH% across different areas

As shown in Figure 2, the launch of vaccination tend to reduce WFH% in Micropolitan and Rural areas but has little impact on WFH% in Metropolitan areas, suggesting a discrepancy between the recovery of normal work mode between these areas, due to the nature of jobs and economic structures. Micropolitan and Rural areas are heavily reliant on sectors that cannot easily adapt to WFH, e.g., agriculture, manufacturing, and thus can see a sharper decline in WFH% as vaccination rates rise. While in Metropolitan areas, after adapting to WFH during the pandemic, many companies are known to have formalized remote working policies due to perceived benefits, such as reduced overhead costs, greater worker flexibility, and increased productivity in many cases. Many employees might prefer the flexibility and convenience it offers, and these structural changes and preferences persist even as vaccination rates increase (Hensher et al., 2023).

Table 3 summarizes the descriptive statistics of the impact for WFH% in the three areas during the post-intervention period. The average relative impact of vaccination on WFH% are −10.7% (St.d.: 7.1%, Median: -13.9%), -14.3% (St.d.: 7.0 %, Median: -14.4%), and -17.5% (St.d.: 9.1%, Median: -18.6 %) in Metropolitan, Micropolitan, and Rural areas, respectively.

Table 3: Descriptive statistics of the impact of vaccination on WFH%

	Metropolitan Areas			Micropolitan Areas			Rural Areas		
	Mean	Std.	Median	Mean	Std.	Median	Mean	Std.	Median
Actual Response (%)	28.90	3.73	28.34	31.25	3.66	34.35	32.19	4.76	33.35
Prediction (%)	32.35	3.68	34.75	36.48	5.66	34.90	39.02	6.89	36.41
Prediction Lower (95%)	16.914	1.58	17.87	15.73	1.54	16.76	17.03	2.01	21.66
Prediction Upper (95%)	45.36	5.82	81.76	72.18	17.26	78.65	76.43	18.56	58.96
Piecewise Effect (%)	-3.45	2.80	-6.62	-5.23	3.05	-7.7	-6.83	3.98	-11.3
Relative Effect	-10.7%	7.1%	-13.9%	-14.3%	7.0%	-14.4%	-17.5%	9.1%	-18.6%
Posterior Probability	0.063	0.021	0.024	0.067	0.057	0.031	0.002	0.042	0.013

Figure 3 presents a comprehensive comparative visualization of relative impact on WFH%, emphasizing the distinct impacts of vaccination on the resilience of WFH% across varied geographical areas. Overall, the vaccination intervention has a negative relative impact on WFH% due to increased confidence in workplace safety or organizational decisions to revert to pre-pandemic working conditions and contribute to the recovery of normal work mode. Figure 4 displays the distribution of relative impact on WFH%, reaching a peak at -22%, -21%, and -27% in Metropolitan, Micropolitan, and Rural areas, respectively. However, the presence of positive values in the range indicates exceptions, with some counties experiencing an increase in WFH% during the post-intervention period.

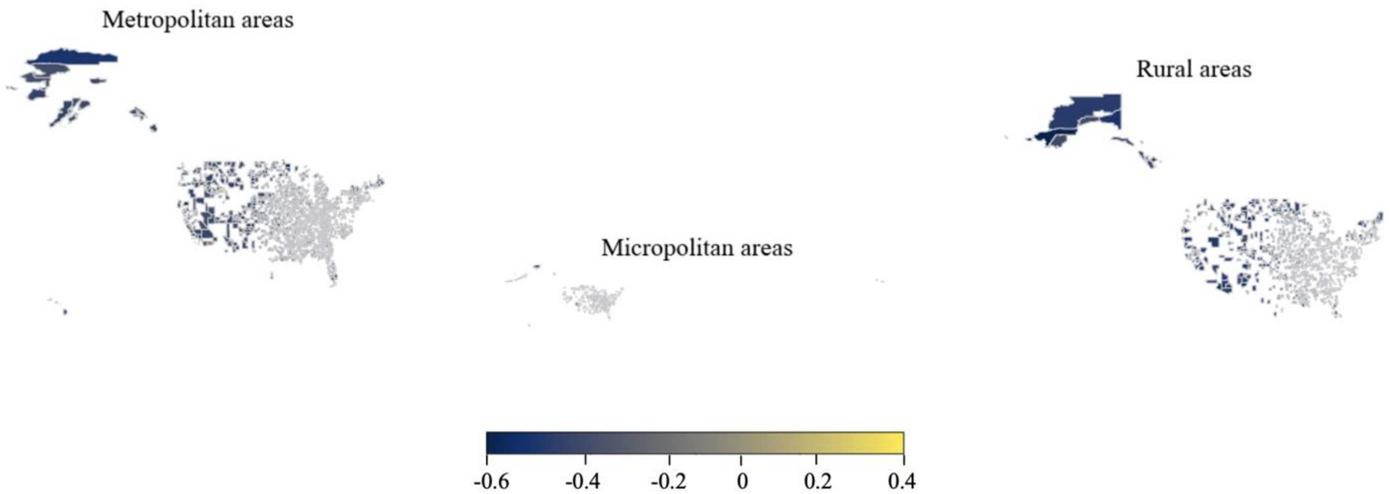


Figure 3. The mean relative effect of vaccination on WFH% across different areas

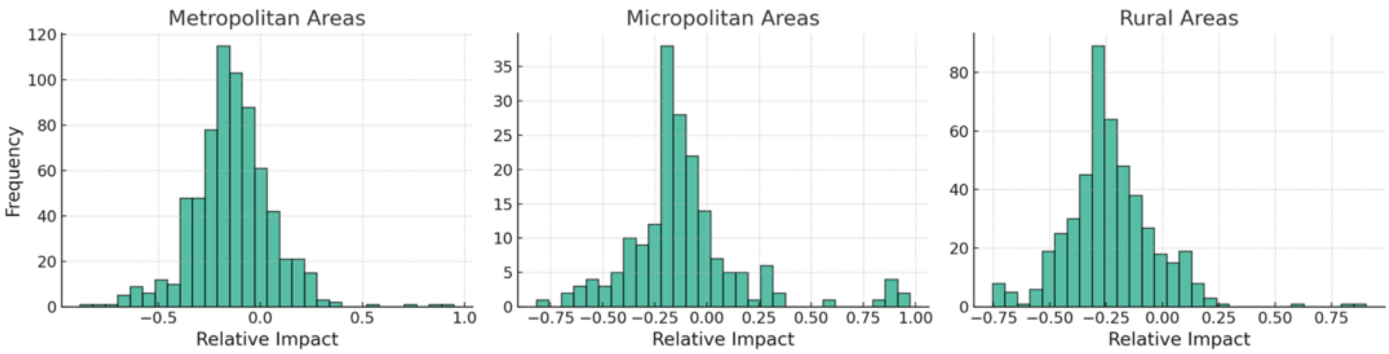
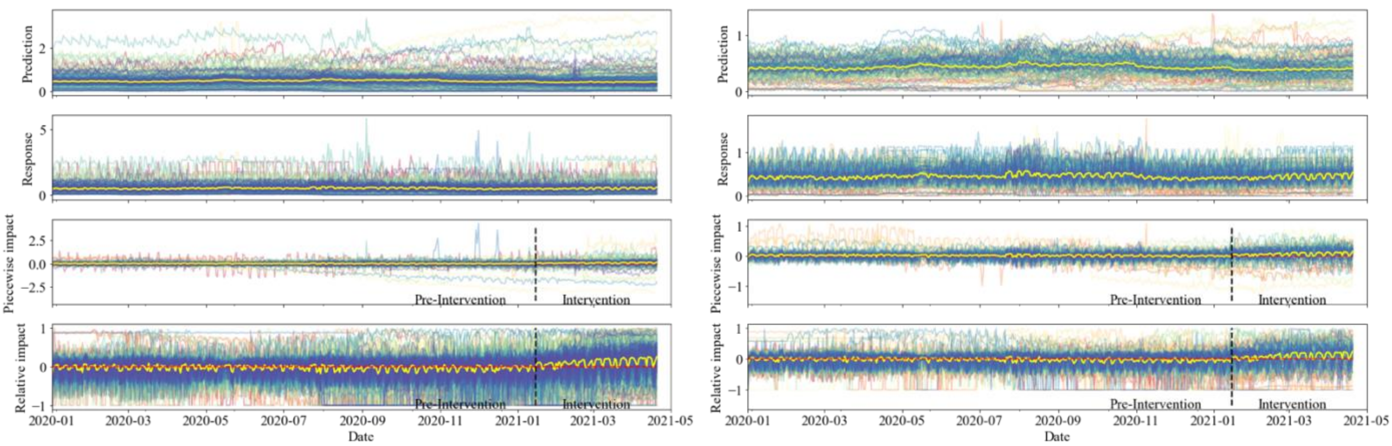


Figure 4. The distribution of mean relative impact of vaccination on WFH% across different areas

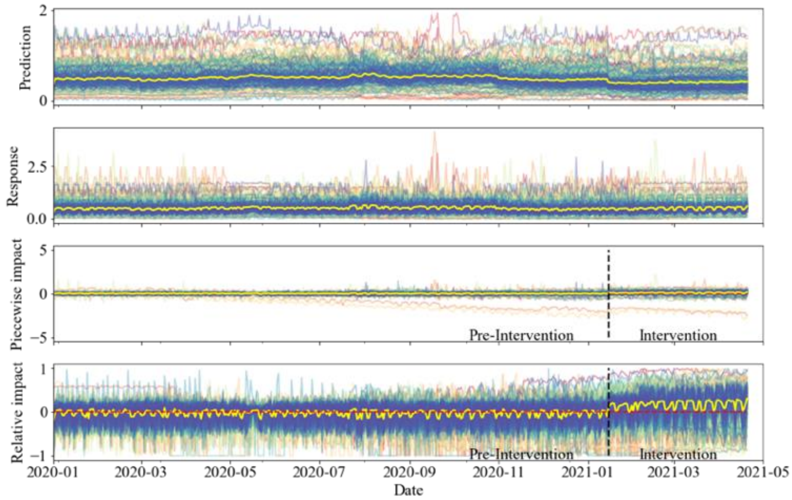
4.1.2 Inferential analysis on work trips

The actual response of work trips in Metropolitan areas was initially averaged at 0.471 during pre-intervention period and displayed a stable recovery trend, marginally dropping to 0.469 during post-intervention period. Work trips in Micropolitan areas began with an average of 0.482 during pre-intervention period, which rose slightly to 0.494 during the post-intervention period, suggesting a more active recuperation. Rural areas, however, demonstrated the most robust recovery in work trips, with the initial average of 0.492 work trips per person prior to vaccination interventions increased to 0.494 during the post-intervention period (Figure 5). The resilience in work trips, especially in less urbanized areas, suggests an adaptive workforce and a greater need or pressure to maintain physical work attendance.

Table 4 summarizes the descriptive statistics of the impact for work trips in three areas during the post-intervention period. The average relative impact of vaccination on work trips are 20.8% (Std.: 9.01%, Median: 11.2%), 11.4% (Std.: 8.7%, Median: 8.8%), and 16.1% (Std.: 8.8%, Median: 19.7%) in Metropolitan, Micropolitan, and Rural areas, respectively.



(a) Work trips in Metropolitan areas (b) Work trips in Micropolitan areas



(c) Work trips in Rural areas

Figure 5. County-level impact of vaccination implementation on work trips across different areas

Table 4: Descriptive statistics of the impact of vaccination on work trips

	Metropolitan Areas			Micropolitan Areas			Rural Areas		
	Mean	Std.	Median	Mean	Std.	Median	Mean	Std.	Median
Actual Response	0.48	0.052	0.48	0.44	0.05	0.51	0.50	0.06	0.52
Prediction	0.38	0.08	0.37	0.39	0.13	0.40	0.42	0.09	0.40
Prediction Lower (95%)	0.11	0.011	0.16	0.06	0.01	0.08	0.21	0.01	0.18
Prediction Upper (95%)	0.68	0.33	0.58	0.55	0.34	0.64	0.78	1.11	0.74
Piecewise Effect	0.10	0.12	0.09	0.05	0.04	0.10	0.08	0.051	0.10
Relative Effect	20.8%	9.01%	11.2%	11.4%	8.7%	8.8%	16.1%	8.8%	19.7%
Posterior Probability	0.023	0.034	0.033	0.022	0.011	0.024	0.032	0.043	0.019

Figure 6 presents a comprehensive comparative visualization of relative impact on work trips, emphasizing the distinct impacts of vaccination on the resilience of work trips across the varied geographical areas. Most of the relative impact on work trips across three areas are concentrated between -0.2 and 0.5, and the average relative impact of vaccination on work trips is positive, suggesting that, on average, vaccination has increased work trips across three areas. Furthermore, as shown in Figure 7, the broad spread of the distribution of relative impact on work trips indicates a diverse range of impacts across different counties. The relative impact on work trips in Metropolitan and Micropolitan areas tend to have a central tendency around 10%, while have a slightly higher central tendency around 20% in Rural areas. The presence of outliers, especially in the negative direction, in all three areas suggests that there might be unique challenges or circumstances in specific counties, which requires a more localized approach to understand and improve the overall effectiveness of vaccination scheme. On average, the vaccination implementation has positively promoted the work trips across three areas, with Rural areas standing out with a higher median due to reasons such as higher demand for in-person labor.

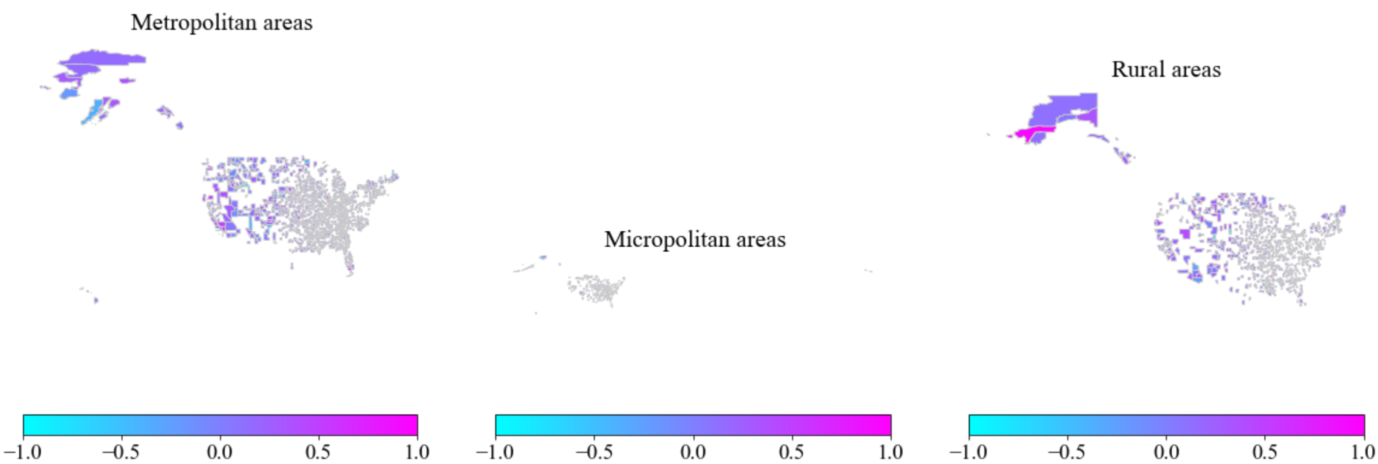


Figure 6: The mean relative impact of vaccination on work trips across different areas

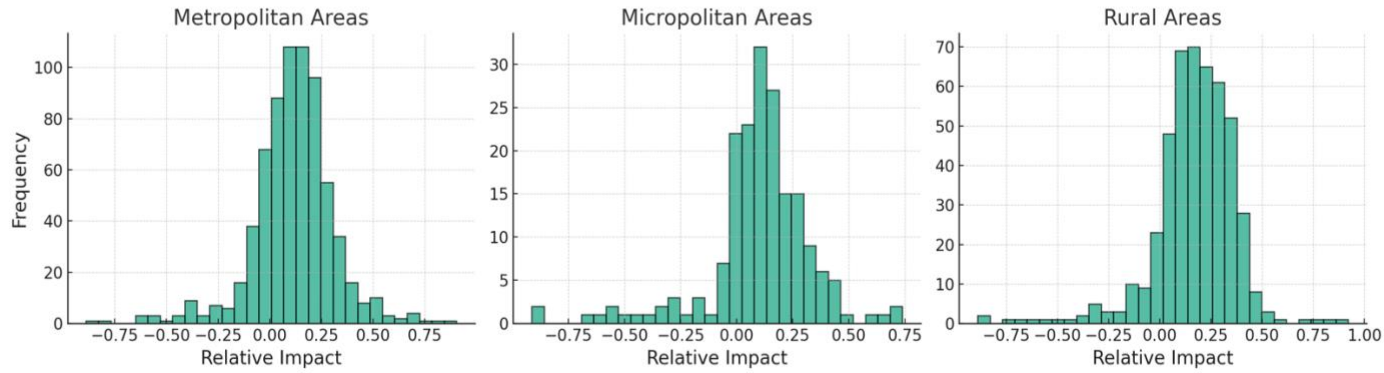
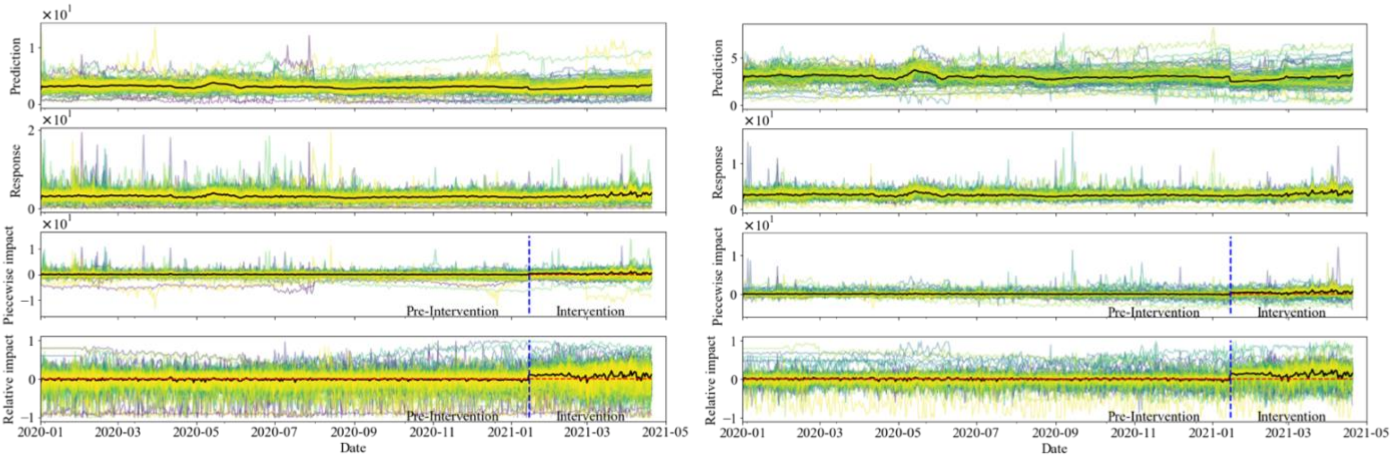


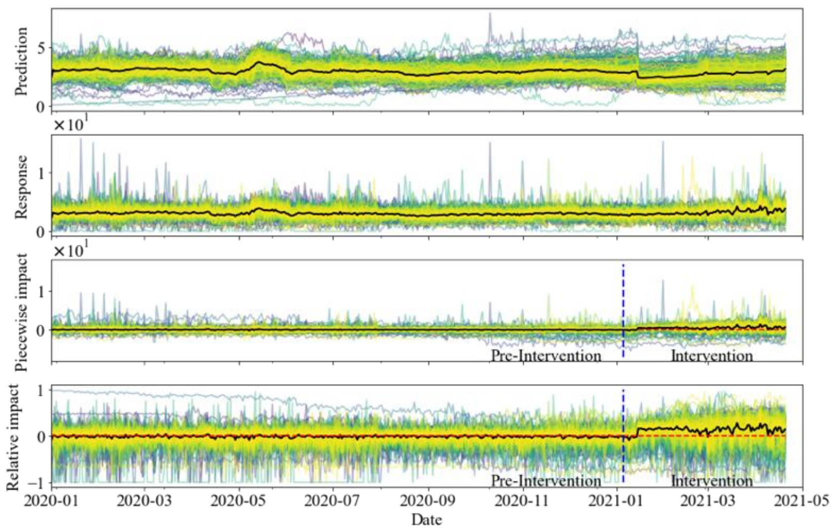
Figure 7: The distribution of the mean relative effect of vaccination on work trips across different areas

4.1.3 Inferential analysis on nonwork trips

In Metropolitan areas, nonwork trips per person exhibited a moderate recovery, rising from an average of 3.076 before vaccination to 3.238 after vaccination. Micropolitan areas exhibited a similar pattern, with nonwork trips per person increasing from 3.042 pre-vaccination to 3.250 post-vaccination, indicating a re-engagement with nonwork activities. In contrast, nonwork trips in Rural areas, started from an average of 3.042 pre-vaccination, exhibited a more pronounced recovery trend, surging to 3.273 post-vaccination (Figure 8). The data showed that while all three areas demonstrated resilience in nonwork trips, the resilience was most evident in Rural areas. The disparities among the three areas potentially reflect differences in community engagement, access to recreational or essential services, or varying degrees of pandemic-related restrictions. The robust recovery trend in Rural areas underscores the importance of nonwork travel in less urbanized areas, due to intrinsic community ties, etc.



(a) Nonwork trips in Metropolitan areas (b) Nonwork trips in Micropolitan areas



(c) Nonwork trips in Rural areas

Figure 8. County-level impact of vaccination implementation on nonwork trips across different areas

Table 5 summarizes the descriptive statistics of the impact for nonwork trips in the three areas during the post-intervention period. The average relative impact of vaccination on nonwork trips are 9.32% (Std.: 20.58%, Median: 11.7%), 13.04% (Std.: 21.7%, Median: 15.56%), and 16.2% (Std.: 20.5%, Median: 17.7%) in Metropolitan, Micropolitan, and Rural areas, respectively.

Table 5: Descriptive statistics of the impact of vaccination on nonwork trips

	Metropolitan Areas			Micropolitan Areas			Rural Areas		
	Mean	Std.	Median	Mean	Std.	Median	Mean	Std.	Median
Actual Response	3.22	0.79	3.15	3.22	0.77	3.14	3.21	0.79	3.15
Prediction	2.92	0.72	2.84	2.80	0.76	2.72	2.69	0.63	2.60
Prediction Lower (95%)	0.38	0.55	1.52	0.02	0.11	1.54	0.27	0.31	1.41
Prediction Upper (95%)	6.51	5.5	5.33	7.41	0.89	5.45	8.82	1.34	5.32
Piecewise Effect	0.3	0.82	0.36	0.42	0.82	0.48	0.52	0.78	0.54
Relative Effect	9.32%	20.58%	11.7%	13.04%	21.7%	15.56%	16.2%	20.5%	17.9%
Posterior Probability	0.083	0.051	0.042	0.065	0.087	0.036	0.067	0.073	0.048

Figure 9 presents a comprehensive comparative visualization of the relative impact on nonwork trips, emphasizing the distinct impact of vaccination on the resilience of nonwork trips in varied geographical areas. In general, the relative impact of vaccination on nonwork trips is positive across all diverse areas, suggesting that vaccination can contribute to an increase in nonwork trips. This indicates that people felt more secure or were more inclined to undertake nonwork trips, perhaps for leisure, shopping, or socializing during the post-vaccination period. As shown in Figure 10, Rural areas consistently exhibited the highest average and median impacts, implying that nonwork trips in Rural areas were more influenced by vaccination efforts, while Metropolitan areas have the lowest average impact and a median closer to the Micropolitan areas.

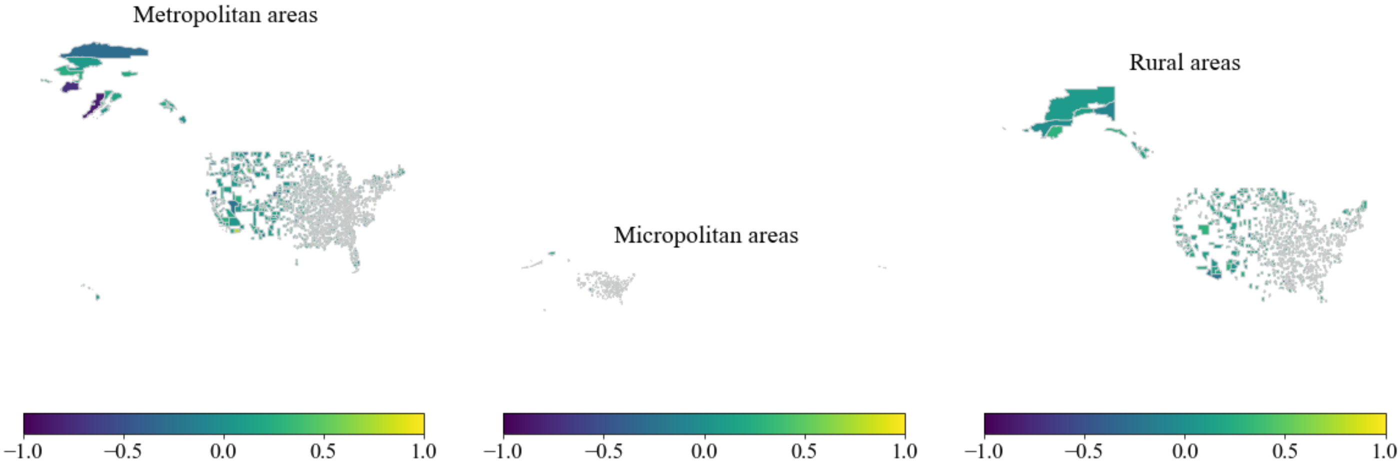


Figure 9. The mean relative effect of vaccination on nonwork trips across different areas

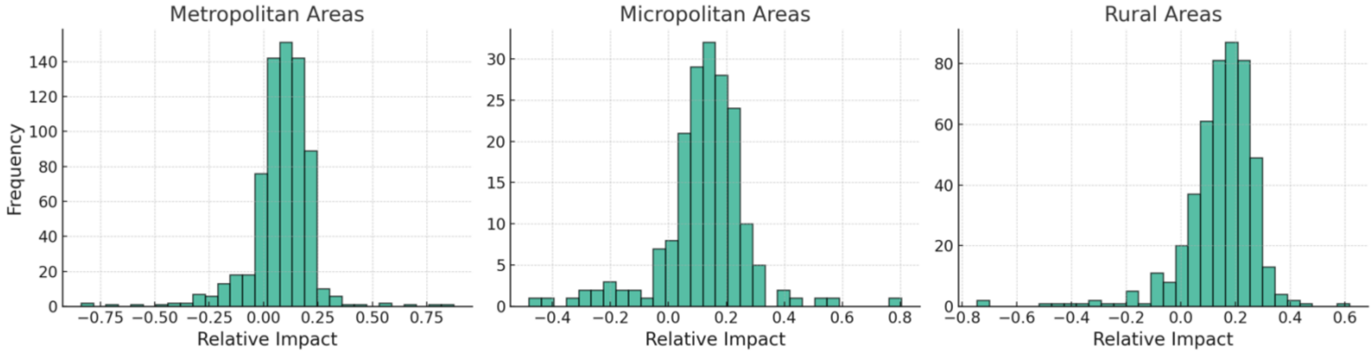
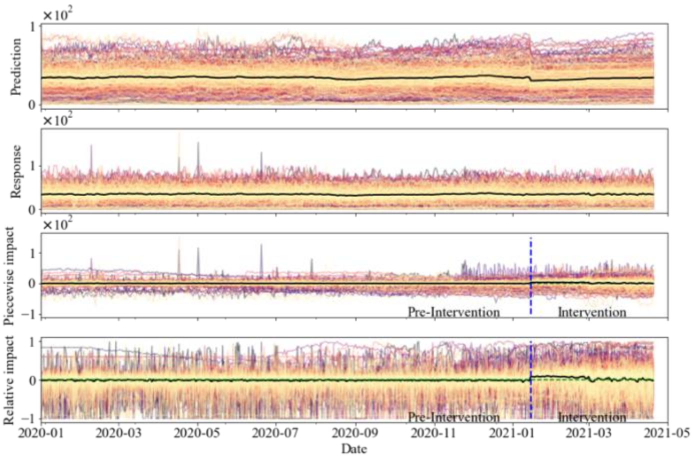


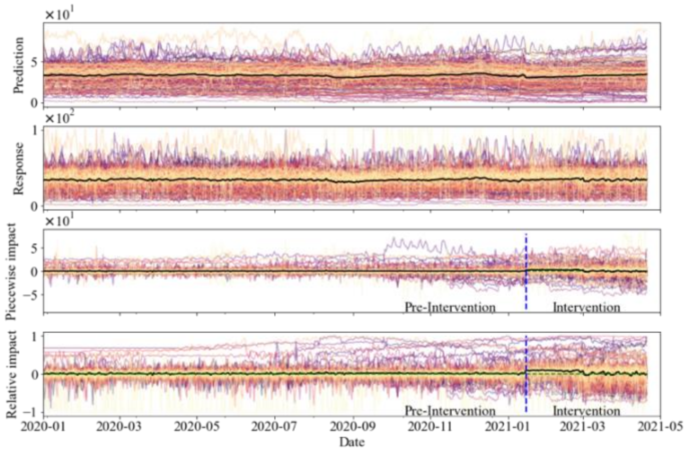
Figure 10. The distribution of the mean relative effect of vaccination on nonwork trips across different areas

4.1.4 Inferential analysis on out-of-county trips

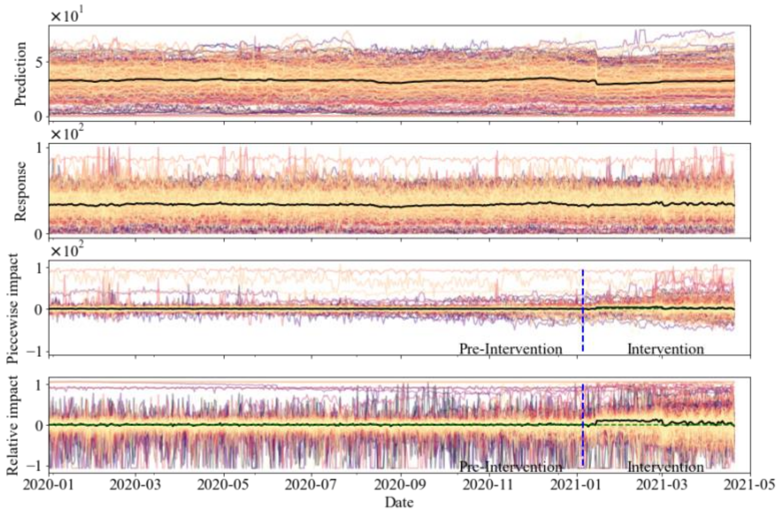
In Metropolitan areas, out-of-county trips% slightly increased from 33.96% pre-vaccination to 34.05% post-vaccination. Micropolitan areas saw a stronger recovery trend, with out-of-county trips% increasing from 35.32% before vaccination to 35.76% after vaccination. However, it was the Rural areas that stood out with a higher base of 34.88% pre-vaccination and a slightly stronger recovery to 34.98% post-vaccination (Figure 11). These trends indicate that while all areas displayed some extent of recovery in out-of-county travel, Micropolitan areas exhibited the most pronounced upward shift. The data reflect regional economic interdependencies, the distribution of essential services, or leisure-related travel behaviors. The resilience in Micropolitan areas highlights the critical role of these areas as bridges between Metropolitan and Rural areas.



(a) Out-of-county trips% in Metropolitan areas



(b) Out-of-county trips% in Micropolitan areas



(c) Out-of-county trips% in Rural areas

Figure 11. County-level impact of vaccination implementation on out-of-county trips% in different areas

Table 6 summarizes the descriptive statistics of the impact for out-of-county trips% in the three areas during the post-intervention period. The average relative impact of vaccination on out-of-county trips% are 4.72% (Std.: 24.59%, Median: 8.67%), 4.9% (Std.: 25.6%, Median: 6.2%), and 7.96% (Std.: 25.06%, Median: 8.48%) in Metropolitan, Micropolitan, and Rural areas, respectively.

Table 6: Descriptive statistics of the impact of vaccination on out-of-county trips

	Metropolitan Areas			Micropolitan Areas			Rural Areas		
	Mean	Std.	Median	Mean	Std.	Median	Mean	Std.	Median
Actual Response	34.12	12.28	34.7	34.17	12.38	35	33.87	12.0	33.9
Prediction	32.51	12.15	32.67	32.48	12.72	33.29	31.17	11.7	31.24
Prediction Lower (95%)	9.64	6.56	21.04	2.45	107.26	19.09	0.14	2.6	19.82
Prediction Upper (95%)	65	32.54	51.91	72.62	84.98	51.78	70.38	13.8	50.33
Piecewise Effect	1.61	9.78	2.77	1.69	10.82	1.92	2.7	10.81	2.60
Relative Effect	4.72%	24.59%	8.67%	4.9%	25.60%	6.2%	7.97%	25.06%	8.48%
Posterior Probability	0.035	0.025	0.028	0.013	0.056	0.019	0.069	0.097	0.089

Figure 12 presents a comprehensive comparative visualization of the relative impact on out-of-county trips, emphasizing the distinct impact of vaccination intervention on the resilience of cross-border travel in varied geographical areas. Across all three areas, relative impact displays a trend of positive values, suggesting that, on average, out-of-county trips% increased since the intervention of vaccination. The relative impact on out-of-county trips% is the greatest in Rural areas and the lowest in Metropolitan areas, indicating that those in Rural areas felt exceptionally constrained by the pandemic and were eager for out-of-county travel once vaccinated. As shown in Figure 13, the mean relative impacts in the three areas exhibited a similar distribution, suggesting that the vaccination scheme would positively impact out-of-county trips% in most counties during the post-intervention period.

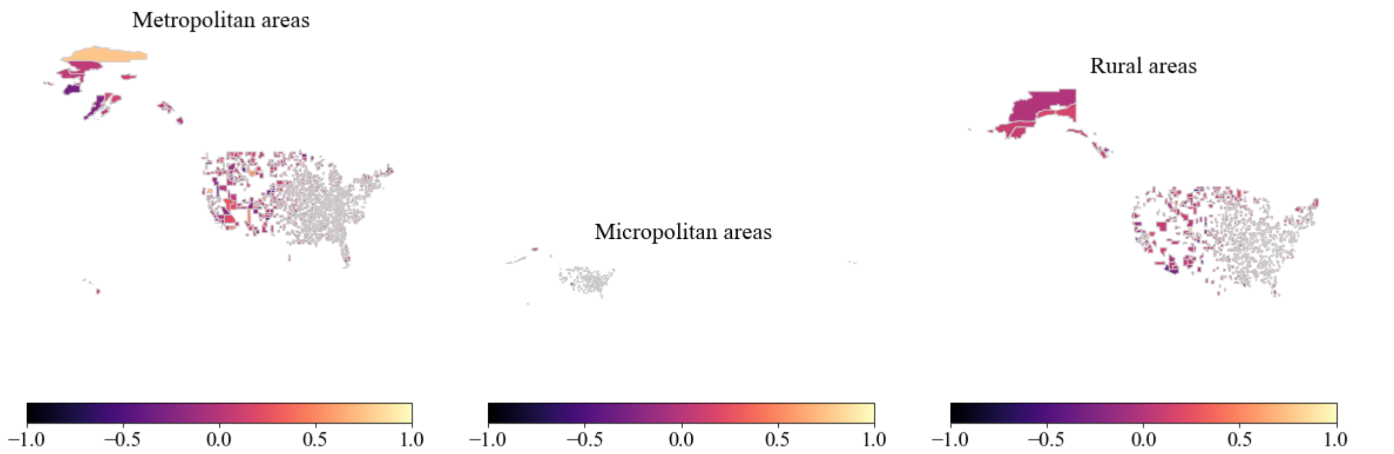


Figure 12. The mean relative effect of vaccination on out-of-county trips across different areas

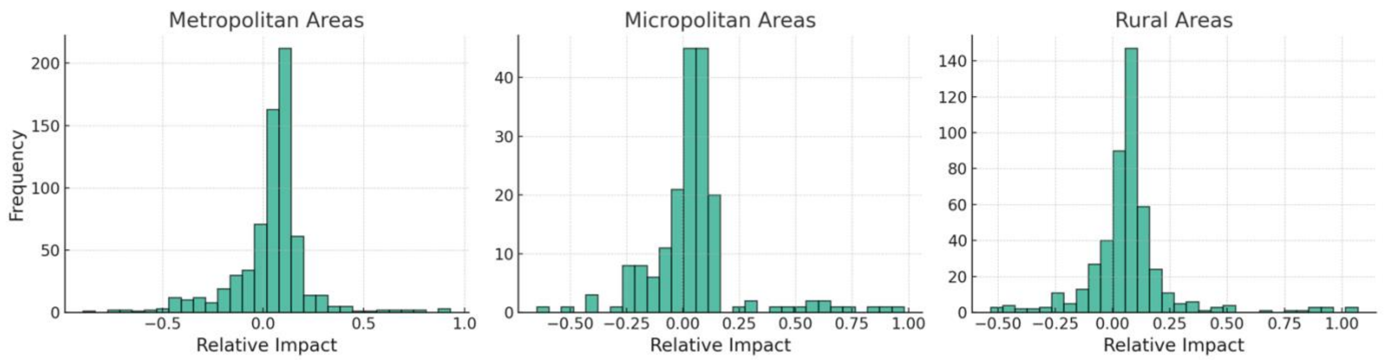
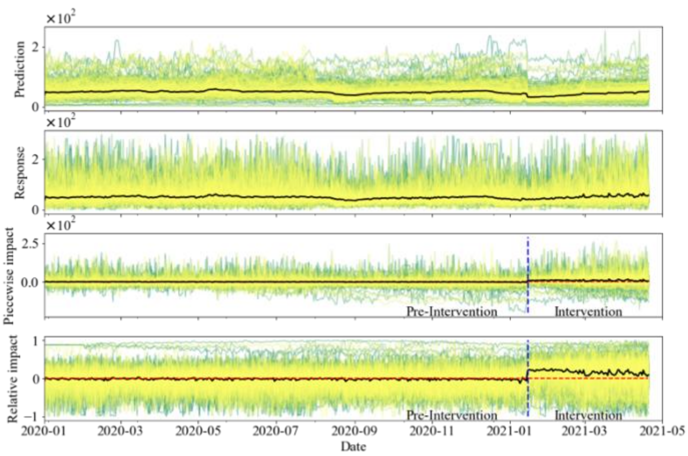


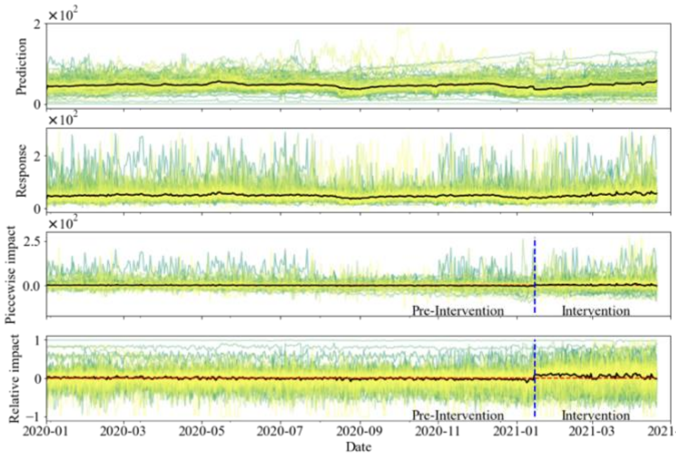
Figure 13. The distribution of the mean relative impact of vaccination on out-of-county trips across different areas

4.1.5 Inferential analysis on travel miles

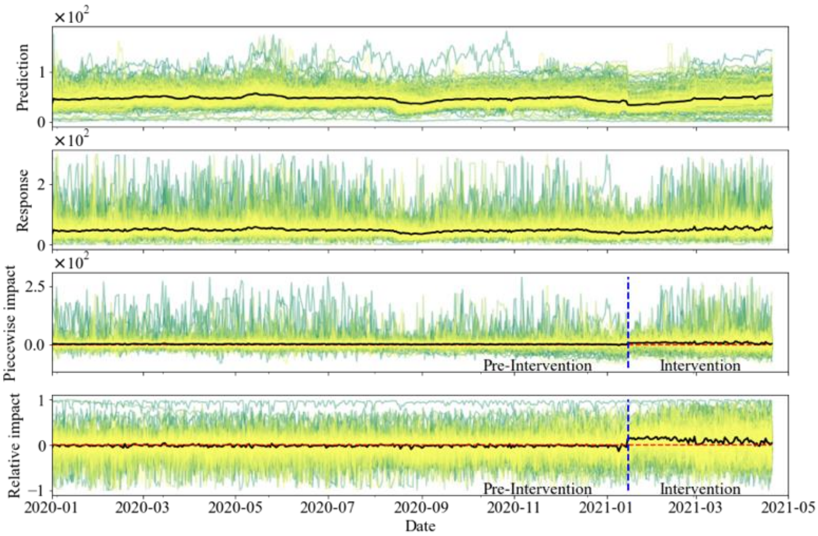
After implementing vaccination scheme, the average travel miles per person in Metropolitan area advanced from 49.57 miles to 51.65 miles, while Micropolitan areas displayed an uptick, with travel miles per person growing from 47.34 miles to 50.16 miles, and Rural areas exhibited a recovery from 47.64 miles to 50.41 miles. The consistent rise of travel miles across three areas could be attributed to economic rejuvenation, easing of travel restrictions, or increased confidence (Figure 14).



(a) Travel Miles in Metropolitan areas



(b) Travel Miles in Micropolitan areas



(c) Travel Miles in Rural areas

Figure 14. County-level impact of vaccination on travel miles across different areas

Table 7 summarizes the descriptive statistics of the impact for travel miles in the three areas during the post-intervention period. The average relative impact of vaccination on travel miles are 18.64% (Std.: 25.52%, Median: 21.08%), 6.71% (Std.: 27.95%, Median: 8.37%), and 12.0% (Std.: 25.40%, Median: 13.48%) in Metropolitan, Micropolitan, and Rural areas, respectively.

Table 7: Descriptive statistics of the impact of vaccination on travel miles

	Metropolitan Areas			Micropolitan Areas			Rural Areas		
	Mean	Std.	Median	Mean	Std.	Median	Mean	Std.	Median
Actual Response	50.47	23.20	46.20	49.89	22.22	45.8	49.21	21.57	45.40
Prediction	41.06	18.44	37.42	46.54	18.65	44.05	43.31	17.21	40.56
Prediction Lower (95%)	0.52	12.35	14.11	0.31	107.40	14.23	0.49	11.34	14.06
Prediction Upper (95%)	122.41	67.82	95.21	157.31	142.48	95.32	116.83	152.26	92.19
Piecewise Effect	0.19	20.47	8.95	3.35	22.76	3.54	5.9	20.17	5.50
Relative Effect	18.64%	25.52%	21.08%	6.71%	27.95%	8.37%	12.0%	25.40%	13.48%
Posterior Probability	0.072	0.045	0.067	0.067	0.056	0.031	0.073	0.047	0.046

Figure 15 offers a comprehensive comparative visualization, emphasizing the distinct impacts of vaccination on the recovery of travel miles across varied geographical areas. There is a discernible trend of positive values, suggesting that, on average, vaccination positively impacts travel miles during the post-vaccination period. As shown in Figure 16, the distribution in Metropolitan, Micropolitan, and Rural areas display a peak of around 20%, 5%, and 10%, implying that vaccinations have played a role in bolstering people's confidence to travel farther distances across three areas. The relative impact on travel miles is the highest in the Metropolitan area where individuals undertake more business travel and visits to places of interest after getting vaccinated.

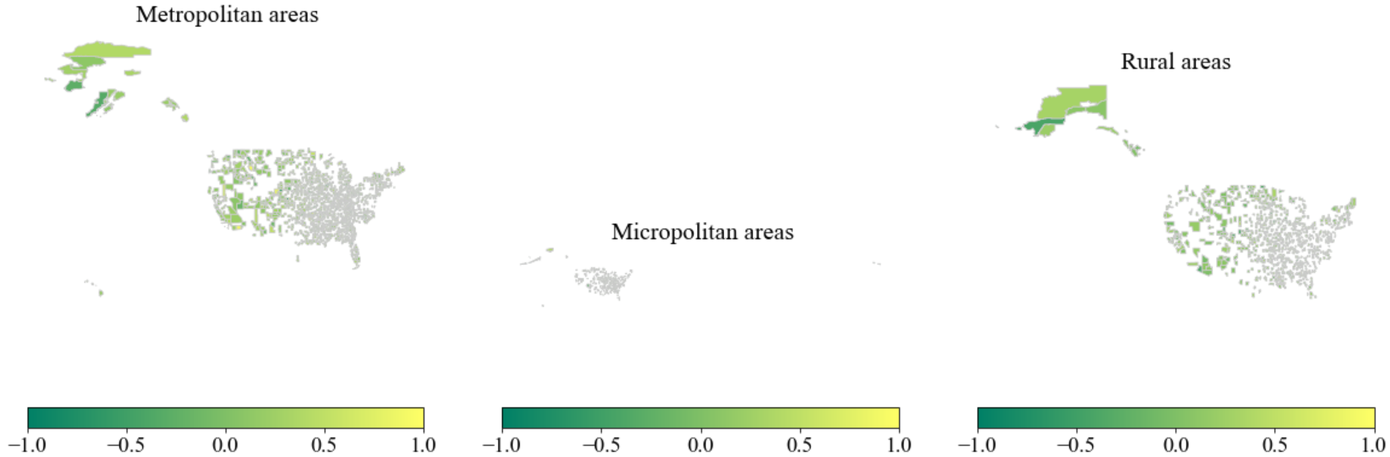


Figure 15. The mean relative effect of vaccination on travel miles across different areas

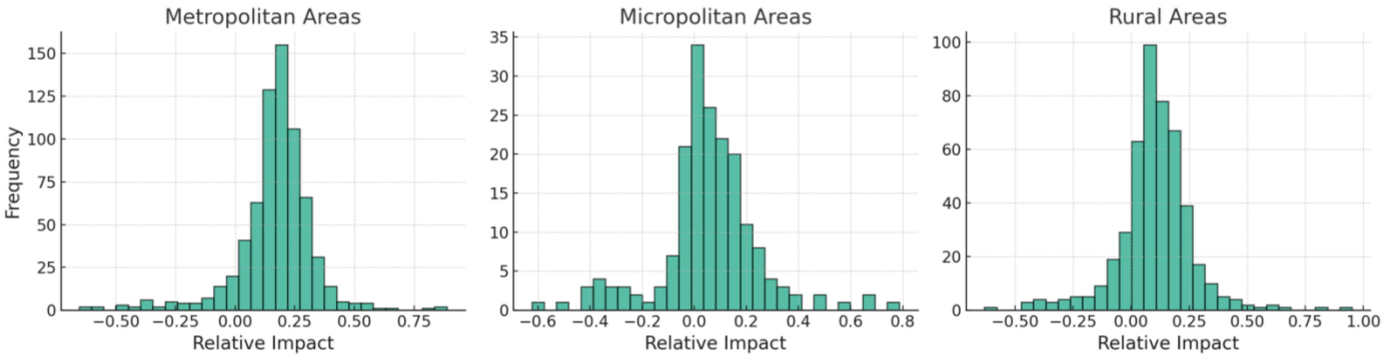


Figure 16. The mean relative effect of vaccination on travel miles across different areas

4.2 Results of PLSR models

BSTS models have inferred the relative impact of vaccination on travel behaviors and initially identified the most influential covariates affecting travel behavior resilience. To further measure the magnitude and significance of these influential factors on five types of travel behavior resilience, we develop PLSR models where the vaccination rates are integrated as an independent variable, except for the covariates in BSTS models. Given the inherent limitations of applying the PLSR model directly to time series data, we compute the monthly mean values for each variable from February 2021, when the vaccination scheme has been launched in 1300 US counties in the dataset. We develop distinct PLSR models for each travel behavior in February, March, and April 2021. The results of the PLSR models are reported in Table 8 - Table 12, where the Goodness-of-fit indexes (R2 (CV)) and RMSE (CV) show that the PLSR models fit the data well. We next analyze the results of PLSR models and provide insights into the impact of vaccination, COVID-19 epidemiological indicators, and weather conditions on the five types of travel behavior, considering the dynamics over the post-vaccination period.

4.2.1 Impact on WFH: vaccination, epidemiological indicators, and weather

Table 8 shows that an increase in *COVID incidence rates* have a positive impact on *WFH%* in Metropolitan and Micropolitan areas, e.g., suppose *the COVID incidence rate*s increase by 10%, *WFH%* is expected to rise by 0.77% in Metropolitan areas and 0.86% in Micropolitan areas in February 2021, while it will see few impacts in Rural areas. This could be explained by various factors such as the nature of work, the availability of remote work options, access to technology and infrastructure, and industry-specific work requirements. In metropolitan and micropolitan areas where there may be a higher concentration of office-based jobs and access to technology, an increase in new COVID cases could lead to more companies adopting remote work policies as a way to reduce the risk of virus transmission and maintain business continuity. On the other hand, in Rural areas where industries may be more labor-intensive and less reliant on technology, the impact of COVID new cases on adopting WFH may be less pronounced.

As the *vaccination rates* increase, *WFH%* will decrease, and there may be a push to return to pre-pandemic levels of work and social activities, e.g., suppose *the vaccination rates* increase by 10%, *WFH%* in Metropolitan, Micropolitan, and Rural areas will see a decrease of 1.41%, 1.59% and 2.04% in February 2021. This indicates that vaccination plays a significant role in restoring people's confidence in returning to their workplaces and resuming pre-pandemic activities, particularly in Rural areas, where agriculture, mining, or manufacturing might be more prevalent, and these industries often require physical presence at the worksites. Suppose *the COVID death rates* increases by 10%. WFH% in Metropolitan, Micropolitan, and Rural areas will see a 3.22%, 2.97%, and 2.77% increase in February 2021 and a 3.65%, 3.51%, and 3.21% increase in March 2021. As the COVID death rates rise, individuals in Metropolitan and Rural areas may be more fearful of contracting the virus and may be more likely to prioritize their health over other considerations.

Suppose *COVID testing rates* increases by 10%, *WFH%* in Metropolitan, Micropolitan, and Rural areas, will see a 1.97%, 2.12%, and 2.17% decrease in April 2021. In response to higher *testing rates*, governments and employers may revise their guidelines and policies regarding remote work. If testing results show lower COVID-19 transmission rates in certain areas, authorities may encourage or require more in-person work, leading to a decrease in *WFH%*.

It is shown that weather conditions such as rain or snow could impact *WFH%* in Rural areas but may have little to no impact on those living in Metropolitan areas. This implies that people in Rural areas may have to travel longer distances and face more challenging road conditions when commuting to work, making it more difficult to travel during inclement weather. Additionally, Rural areas have less developed infrastructure and public transport systems, which could further limit people's ability to travel to work during bad weather. In contrast, individuals living in metropolitan areas often have greater flexibility to work from home, making them less impacted by weather conditions when it comes to their work arrangements.

Table 8: Results of PLSR model for WFH% across Metropolitan, Micropolitan and Rural areas

	February 2021			March 2021			April 2021		
	Metropolitan areas	Micropolitan areas	Rural areas	Metropolitan areas	Micropolitan areas	Rural areas	Metropolitan areas	Micropolitan areas	Rural areas
COVID incidence rate	0.077**	0.086**	0.097	0.054*	0.024	0.002	0.152**	0.138***	0.107
Vaccination rate	-0.141***	-0.159***	-0.204***	-0.232***	-0.239***	-0.259***	-0.234***	-0.245***	-0.264***
COVID death rate	0.322***	0.297***	0.277***	0.365***	0.351***	0.321***	0.327***	0.320***	0.312***
COVID testing rate	-0.144***	-0.152***	-0.161**	-0.181***	-0.200***	-0.205***	-0.197***	-0.212***	-0.217***
Temperature	0.020	0.033	0.061	-0.005	0.000	0.012	0.059	0.061	0.061
Rain frequency	-0.013	-0.001	0.030*	-0.041	-0.046	-0.036	0.039	0.042	0.045*
Snow frequency	0.008	-0.005	0.026*	0.029	0.001	0.048***	0.084*	0.072**	0.073**
R^2	0.622 (CV:0.602)	0.608 (CV:0.582)	0.613 (CV:0.596)	0.547 (CV:0.535)	0.548 (CV:0.518)	0.521 (CV:0.502)	0.667 (CV:0.644)	0.632 (CV:0.613)	0.644 (CV:0.626)
RSME	0.428 (CV: 0.430)	0.409 (CV: 0.411)	0.380 (CV:0.383)	0.446 (CV: 0.450)	0.448 (CV: 0.452)	0.444 (CV: 0.448)	0.525 (CV:0.528)	0.527 (CV: 0.5303)	0.518 (CV: 0.522)

Notes:
a. Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05
b. R^2 0.622 (CV: 0.428) means the R^2 for WFH% in Metropolitan area in February is 0.622 with 10-fold cross-validation value is 0.428.
c. RSME 0.428 (CV: 0.430) means the RSME for WFH% in Metropolitan area in February is 0.428 with 10-fold cross-validation value is 0.430.

4.2.2 Impact on work/nonwork trips: vaccination, epidemiological indicators, and weather

Table 9 and Table 10 show that certain public health metrics (i.e., COVID vaccination rates, testing rates, and death rates) are more influential in shaping work/nonwork trips than the COVID incidence rates. The number of *work/nonwork trips* is not impacted by an increase in *new COVID cases*, while an increase in *vaccination rates* has a positive impact on *work/nonwork trips*, especially in Micropolitan and Rural areas. For instance, a 10% increase in *vaccination rates* can result in an increase of 0.13% (resp. 0.44%) and 0.48 (resp. 0.53%) in *work trips* (resp. *nonwork trips*) for Micropolitan and Rural areas in February 2021. However, *work trips* in Metropolitan areas impact may not be significantly impacted since people have already adjusted their work patterns to include remote work and may continue to do so even as *vaccination rates* increase. As more people become vaccinated, individuals are more willing to engage in nonwork-related activities, such as social outings, shopping, and leisure, leading to an increase in *nonwork trips*. For instance, as *vaccination rates* increase by 10%, the *nonwork trips* in Metropolitan, Micropolitan and Rural areas will see a 0.51%, 0.44%, and 0.53% increase in February 2021.

As *COVID death rates* increase, there will be a decrease in *work/nonwork trips*, e.g., a 10% increase in *COVID death rates* can result in a decrease of 0.51% (resp. 1.25%), 0.64% (resp.1.44%), and 0.79% (resp. 1.8%) in *work trips* (resp. *nonwork trips*) for Micropolitan, Micropolitan, and Rural areas, in April 2021. One possible reason is that higher death rates may lead to greater public fear and concern, causing people to be more cautious about travel and public gatherings. Additionally, companies may implement remote work policies to protect their employees and prevent the spread of the virus as *COVID death rates* increase. This is consistent with the results show in Table 8, namely, as *Covid death rates* increase, *WFH%* will be increased.

As *COVID testing rates* increase, the number of *work trips/nonwork trips* will increase in Metropolitan and Micropolitan areas but may decrease in Rural areas, e.g., suppose *testing rates* increase by 10%, the number of *work trips (resp. nonwork trips)* will see a 0.47% (resp. 1.49%) and a 0.57% (resp. 1.46%) increase for Micropolitan and Rural areas, as well as a 0.83% (resp. 1.31%) decrease for Rural areas in March 2021. One possible reason is that the increased *testing rates* may help identify and control outbreaks more effectively in Metropolitan and Micropolitan areas, reducing the perceived risk of transmission and making people feel more comfortable with travel and work. In contrast, limited access to testing and healthcare facilitations in Rural areas may make people more cautious about travel.

According to Table 9, an increased frequency of rain is associated with a decrease in work trips for individuals residing in Micropolitan and Rural areas, e.g., a 10% increase in the *frequency of rain* can result in a decrease of 0.1%, 0.28%, and 0.15% for Rural areas in February, March, and April 2021; Table 10 shows that temperature may influence the number of *non-work trips* taken in Rural areas, but not in Metropolitan or Micropolitan areas. Similarly, a 10% increase in the *frequency of snow* can result in a decrease of 0.21%, 0.58%, 0.44% in *nonwork trips* for Rural areas during the same period, however, it may have no impact on the number of *nonwork trips* in Metropolitan areas. One explanation is that, in Metropolitan areas where public transport is convenient, people may be less affected by weather conditions and are likely to take non-work trips regardless of the weather. In addition, individuals in Rural areas may be more inclined to participate in nonwork activities that are more enjoyable in warmer weather, such as hiking and camping. In contrast, people in Metropolitan areas may have access to more indoor activities, such as museums, theatres, and shopping, which are less affected by weather.

Table 9: Results of PLSR model for work trips across Metropolitan, Micropolitan and Rural areas

	February 2021			March 2021			April 2021		
	Metropolitan areas	Micropolitan areas	Rural areas	Metropolitan areas	Micropolitan areas	Rural areas	Metropolitan areas	Micropolitan areas	Rural areas
COVID incidence rate	0.014	-0.001	0.023	0.044	0.018	-0.013	0.034	0.002	-0.015
Vaccination rate	0.010	0.013**	0.048*	0.014	0.012*	0.042*	0.007	0.024*	0.059*
COVID death rate	-0.094**	-0.058*	-0.041*	-0.059*	-0.060***	-0.054*	-0.051*	-0.064***	-0.079**
COVID test rate	0.051	0.041*	-0.058**	0.047*	0.057**	-0.083**	0.046*	0.060**	-0.097*
Temperature	-0.114	-0.111	-0.121	-0.080	-0.053	-0.026	-0.057	-0.046	-0.046
Rain frequency	-0.092***	-0.091*	-0.100*	-0.009	-0.013	-0.028*	0.019	0.002	-0.015*
Snow frequency	0.043	0.039	-0.038	0.007	0.008	0.018	-0.011	0.015	0.029
R^2	0.621 (CV:0.610)	0.436 (CV:0.439)	0.632 (CV:0.522)	0.489 (CV:0.476)	0.489 (CV:0.476)	0.496 (CV:0.488)	0.567 (CV:0.553)	0.586 (CV:0.567)	0.572 (CV:0.558)
RSME	0.436 (CV:0.439)	0.447 (CV:0.449)	0.444 (CV:0.447)	0.488 (CV:0.493)	0.488 (CV:0.490)	0.482 (CV:0.485)	0.504 (CV:0.506)	0.504 (CV:0.506)	0.491 (CV:0.496)

Notes:

a. Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05

b. R^2 0.621 (CV: 0.610) means the R^2 for work trips in Metropolitan area in February is 0.621 with 10-fold cross-validation value is 0.610.

c. RSME 0.436 (CV: 0.439) means the RSME for work trips in Metropolitan area in February is 0.436 with 10-fold cross-validation value is 0.439.

Table 10: Results of PLSR model for nonwork trips across Metropolitan, Micropolitan and Rural areas

	February 2021			March 2021			April 2021		
	Metropolitan areas	Micropolitan areas	Rural areas	Metropolitan areas	Micropolitan areas	Rural areas	Metropolitan areas	Micropolitan areas	Rural areas
COVID incidence rate	0.071	0.076	0.102	0.004	0.021	0.058	-0.027	-0.032	-0.020
Vaccination rate	0.051*	0.044*	0.053*	0.069**	0.047**	0.027*	0.127**	0.132**	0.115**
COVID death rate	-0.068*	-0.037*	-0.006*	-0.052*	-0.048**	-0.059*	-0.125***	-0.144***	-0.180***
COVID test rate	0.157**	0.140***	-0.150**	0.149***	0.146***	-0.131*	0.143**	0.129***	-0.088*
Temperature	-0.074	-0.040	0.010*	-0.015	0.008	0.049*	0.000	0.037	0.095*
Rain frequency	-0.024	-0.012	-0.007*	0.041	0.037	0.053	0.079	-0.080*	-0.115**
Snow frequency	0.055*	0.031	-0.021*	-0.024	-0.042*	-0.058*	-0.028	-0.046**	-0.044*
R^2	0.625 (CV:0.613)	0.532 (CV:0.477)	0.592 (CV:0.456)	0.576 (CV:0.549)	0.572 (CV:0.554)	0.477 (CV:0.469)	0.612 (CV:0.589)	0.578 (CV:0.558)	0.601 (CV:0.588)
RSME	0.458 (CV: 0.582)	0.461 (CV:0.462)	0.475 (CV:0.479)	0.387 (CV:0.390)	0.397 (CV:0.401)	0.411 (CV:0.412)	0.652 (CV:0.657)	0.635 (CV:0.639)	0.601 (CV:0.611)

Notes:

a. Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05

b. R^2 0.625 (CV: 0.613) means the R^2 for nonwork trips in Metropolitan area in February is 0.625 with 10-fold cross-validation value is 0.613.

c. RSME 0.458 (CV: 0.582) means the RSME for nonwork trips in Metropolitan area in February is 0.458 with 10-fold cross-validation value is 0.582.

4.2.3 Impact on out-of-county trips: vaccination, epidemiological indicators, and weather

Table 11 shows that an increase in *COVID incidence rates* may discourage rural residents from taking *out-of-county trips* due to concerns about transmission and safety. Rural residents may be more likely to travel to neighboring counties for work, shopping, or other essential activities because of limited options available locally. In contrast, individuals living in Metropolitan and Micropolitan areas may have more options available within their own counties and may be less reliant on taking *out-of-county trips*. As a result, an increase in new COVID cases may have a negative impact on out-of-county trips% for individuals living in Rural areas, e.g., a 10% increase in *COVID incidence rates* increase can result in a decrease of 0.24%, 0.1%, and 0.14% of *out-of-county trips%* for Rural areas in February, March, and April 2021, but not for those living in Metropolitan and Micropolitan areas. With more people vaccinated against COVID-19, there may be a greater sense of safety and confidence in traveling outside. As travel and gathering restrictions ease, people may be more inclined to take trips for leisure or to visit friends and family outside of their own counties. In addition, the tourism and hospitality industries may benefit from increased out-of-county travel, leading to economic benefits for local businesses and communities. For instance, a 10% increase in *vaccination rates* can result in an increase of 1.48%, 1.5 %, and 1.6% for *out-of-county trips%* in Metropolitan, Micropolitan, and Rural areas in February 2021.

An increase in *COVID death rates* have little impact on *out-of-county trips%* (Table 11) but could affect the number of *work* and *non-work trips* taken by individuals (Table 9 - Table 10). *COVID death rates* may be seen as a more indirect risk factor for travel, and after prolonged periods of dealing with restrictions and public health measures, some individuals might experience COVID fatigue, and become less willing to change their cross-county travel plans, regardless of the increase in *COVID death rates*. In addition, since a significant portion of the population has vaccinated, they may be less concerned about the impact of COVID. As *COVID testing rates* increase, *out-of-county trips%* will decrease, for instance, a 10% increase in *testing rates* can result in a decrease of 1.6%, 1.57%, and 1.66% in *out-of-county trips%* for Metropolitan, Micropolitan, and Rural areas in February 2021.

It is showed that higher *frequency of rain* or *snow* have a negative impact on *out-of-county trips%* in Rural and Micropolitan areas but have little impact in Metropolitan areas. For instance, a 10% increase in *the frequency of rain* can result in a decrease of 0.19%, 0.69%, and 1.11% in *out-of-county trips* for rural areas in February, March, and April 2021. Table 11 shows that higher *frequency of rain or snow* may have a negative impact on *out-of-county trips%* taken by individuals in Rural or Micropolitan areas but may have little impact on *out-of-county trips%* taken by individuals in Metropolitan areas. Individuals living in Rural or Micropolitan areas face more challenges for traveling out of their counties during inclement weather due to limited road infrastructure and transport options, while individuals living in Metropolitan areas may have more access to more robust public transport, which make it easier for them to take out-of-county trips.

Table 11: Results of PLSR model for out-of-county trips% across Metropolitan, Micropolitan and Rural areas

	February 2021			March 2021			April 2021		
	Metropolitan areas	Micropolitan areas	Rural areas	Metropolitan areas	Micropolitan areas	Rural areas	Metropolitan areas	Micropolitan areas	Rural areas
COVID incidence rate	-0.034	-0.030	-0.024*	0.041	0.026	-0.010*	0.013	0.018	-0.014*
Vaccination rate	0.148**	0.150***	0.166**	0.144***	0.120***	0.111**	0.155***	0.128***	0.111**
COVID death rate	0.086	0.082	0.081	0.046	0.018	-0.008	0.040	0.017	-0.021
COVID test rate	-0.160*	-0.157***	-0.166***	-0.135***	-0.115***	-0.097**	-0.139***	-0.122***	-0.105**
Temperature	0.070	0.052**	0.007	0.032*	0.051**	0.075**	0.037**	0.051*	0.074*
Rain frequency	-0.027	-0.013	-0.019*	0.020	-0.041*	-0.069**	0.019	-0.050*	-0.111*
Snow frequency	0.034	0.013	-0.029*	-0.038	-0.056*	-0.084**	-0.039	-0.065**	-0.128***
R^2	0.612 (CV:0.597)	0.588 (CV:0.569)	0.599 (CV:0.583)	0.601 (CV:0.594)	0.587 (CV:0.566)	0.612 (CV:0.593)	0.587 (CV:0.569)	0.623 (CV:0.602)	0.598 (CV:0.581)
RSME	0.105 (CV:0.107)	0.104 (CV:0.105)	0.102 (CV:0.104)	0.127 (CV:0.129)	0.109 (CV:0.115)	0.104 (CV:0.111)	0.128 (CV:0.217)	0.185 (CV:0.228)	0.146 (CV:0.259)

Notes:
a. Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05
b. R^2 0.612 (CV: 0.597) means the R^2 for out-of-county trips% in Metropolitan area in February is 0.612 with 10-fold cross-validation value is 0.597.
c. RSME 0.105 (CV: 0.107) means the RSME for out-of-county trips% in Metropolitan area in February is 0.105 with 10-fold cross-validation is 0.107.

4.2.4 Impact on travel miles: vaccination, epidemiological indicators, and weather

Table 12 shows that an increase in *COVID incidence rates* may lead to a decrease in travel miles, particularly in Micropolitan rural areas, e.g., a 10% increase in *COVID incidence rates* can result in a decrease of 0.49%, 0.28%, and 0.1% in *travel miles* for Rural areas in February, March, and April 2021. An increase in *Covid incidence rates* could lead to increased restrictions on travel and public gatherings. In Micropolitan and Rural areas with less access to public transportation, these restrictions could lead to a decrease in overall *travel miles*. As *vaccination rates* increase, *travel miles* may increase, particularly in Rural areas, e.g., a 10% increase in *vaccination rates* can result in a decrease of 1.34%, 0.09%, and 0.5% in *travel miles* for Rural areas in February, March, and April 2021. This could be due to a reduced fear of contracting or spreading the virus, as well as fewer restrictions on travel and a greater ability to participate in activities that were previously restricted. This increased confidence and freedom may lead to more travel and longer travel distances in Rural areas. It is noteworthy that the vaccination rates in February 2021 were still relatively low in many counties and may not have had a significant impact on changing users' *travel miles*. However, as *vaccination rates* increase over time, there were more significant changes in *travel miles* in April 2021.

As *COVID testing rates* increase, individuals' travel miles present apparent discrepancy between Rural and Metropolitan areas, e.g., a 10% increase in *vaccination rates* can result in a decrease of 0.99 in *travel miles* for Rural areas and an increase of 0.96% and 0.98% in *COVID testing rates* for Micropolitan and Rural areas in April 2021. In Rural areas, an increase in *COVID testing rates* may be associated with a decrease in *travel miles*, as individuals may be more cautious about travelling if they are aware of higher incidence of COVID-19 in their areas. Additionally, Rural areas may have more limited access to healthcare and testing sites, which could make it more difficult or less desirable to travel for non-essential reasons. In Metropolitan and Micropolitan areas, more individuals may feel comfortable traveling as they receive negative test results and increase their work or other essential trips.

Table 12 shows that an increase in *temperature* may lead to an increase in *travel miles*, especially in Metropolitan and Micropolitan areas, e.g., a 10% increase in *temperature* can result in an increase of 1.47%, 1.13%, 1.18% in *travel miles for* Metropolitan areas in February to April 2021, since warmer weather may encourage people to engage in outdoor activities and travel, such as visiting parks, beaches, or other recreational areas. Additionally, in Metropolitan and Micropolitan areas, warmer weather may lead to increased tourism and travel such as visiting cities and other attractions. It is shown that *the frequency of rain* may have a negative impact on *travel miles*, while *the frequency of snow* may have a positive impact on *travel miles*, due to several reasons. For instance, rain can make driving or walking conditions more dangerous and may discourage people from travelling long distances; heavy rain can lead to flooding or other forms of damage, which can further limit travel options. Conversely, *snow* may encourage people to engage in outdoor activities and travel, such as skiing or visiting winter-themed attractions. In some US counties, snow may also be associated with winter sports or holidays, which can lead to increased tourism and travel.

Table 12: Results of PLSR model for travel miles across Metropolitan, Micropolitan and Rural areas

	February 2021			March 2021			April 2021		
	Metropolitan areas	Micropolitan areas	Rural areas	Metropolitan areas	Micropolitan areas	Rural areas	Metropolitan areas	Micropolitan areas	Rural areas
COVID incidence rate	-0.081**	-0.060**	-0.049*	-0.017	0.007	-0.028*	-0.014	-0.009**	-0.010**
Vaccination rate	0.009	-0.033	0.134***	0.045*	0.039**	0.009*	0.044*	0.054**	0.050*
COVID death rate	-0.010	-0.017	-0.034	-0.047*	-0.064*	-0.116*	-0.100**	-0.116***	-0.148***
COVID test rate	-0.005	-0.023	-0.062**	0.069*	0.058*	-0.048**	0.096**	0.098***	-0.099*
Temperature	0.147***	0.121***	0.089***	0.113**	0.081**	0.053	0.118***	0.077**	0.028
Rain frequency	-0.146***	-0.111***	-0.089*	-0.088***	-0.060**	-0.051	-0.013	-0.012	0.008
Snow frequency	0.049**	0.037**	0.037	0.089**	0.051*	0.019	0.109**	0.049*	-0.007
R^2	0.578 (CV:0.569)	0.545 (CV:0.527)	0.563 (CV:0.548)	0.612 (CV:0.586)	0.623 (CV:0.611)	0.633 (CV:0.623)	0.663 (CV:0.646)	0.612 (CV:0.580)	0.622 (CV:0.601)
RSME	0.211 (CV: 0.279)	0.234 (CV:0.311)	0.217 (CV:0.290)	0.168 (CV:0.223)	0.256 (CV:0.298)	0.278 (CV:0.346)	0.229 (CV:0.304)	0.268 (CV:0.334)	0.256 (CV:0.311)

Notes:
a. Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05
b. R^2 0.578 (CV: 0.569) means the R^2 for travel miles in Metropolitan area in February is 0.578 10-fold cross-validation value is 0.569.
c. RSME 0.211 (CV: 0.279) means the RSME for travel miles in Metropolitan area in February is 0.211 10-fold cross-validation value is 0.279.

5. Policy implication and discussion

Our findings can provide policymakers with evidence-based insights to make informed decisions regarding travel-related policies during future pandemics. Understanding how vaccinations contribute to building the travel behavior resilience and the interrelationship between vaccination rates, epidemiological indicators and travel behavior can guide policymakers in implementing appropriate measures to ensure public safety while promoting the resilience of transportation systems. In particular, recognizing the disparities of travel behavior resilience exhibited between urban and rural areas allows policymakers to tailor interventions and prioritize resource distribution, such as testing facilities, healthcare services, and vaccine distribution, to ensure equitable access and efficient disease containment. Maintaining resilience in travel behavior requires the development of the following policy measures, such as decision support tools and post-disruption recovery strategies that can respond to disruptions and uncertainties.

Promoting vaccination uptake: Our findings confirm that vaccinations can contribute to enhancing the resilience of five distinct types of travel behavior, especially in Rural areas, highlighting the critical need for widespread vaccination coverage and impactful vaccination campaigns. These efforts are essential to restoring public confidence in travel, ensuring fair access to vaccines, and combating vaccine hesitancy, thereby building travel behavior resilience in the face of future pandemics.

Adapting public health message to shifting public perception: Our findings suggest that as the pandemic has continued over time, people may have become desensitized to high COVID case numbers, leading work/nonwork trips to respond less to COVID incidence rates but more to other indicators like death rates and vaccination rates. Policymakers should consider recalibrating public health messaging to emphasize the more salient indicators of COVID-19 severity and control, such as death rates and vaccination rates. For example, campaigns should pivot towards highlighting the real and tragic loss of life associated with higher death rates or emphasizing the personal and community benefits of vaccination.

Flexible work arrangements in Metropolitan areas: Our findings show that individuals in Micropolitan and Rural areas may not easily adapt to WFH, leading to a sharp decline in WFH as vaccination rates increase. In contrast, the incidence of WFH in Metropolitan areas keep being high and exhibit little recovery even with higher vaccination rates. To accommodate the increased incidence of WFH in Metropolitan areas, policymakers should encourage hybrid work models that can provide workforce flexibility, allowing individuals to adapt to evolving health and travel conditions while maintaining productivity. Reduced daily commuting in Metropolitan areas can lead to less congestion but may also result in decreased revenue from public transport tickets and associated services. Future urban transport models need to adjust transport demand prediction and consider land-use changes and their implications on transport planning, e.g., reduced demand for office spaces and increased demand for residential spaces with home offices.

Strengthening healthcare infrastructure in Rural areas: Our findings show that the travel behavior of individuals in Rural areas is more sensitive to vaccination rates, epidemiological indicators, and weather conditions during the recovery period of the pandemic. Metropolitan areas with abundant healthcare resources displayed more robust resilience in travel behavior. Therefore, future policies should strengthen healthcare facilities in Rural areas to ensure access to testing, vaccination, and public transport services. Such investments can enhance the travel behavior resilience of local communities in facing future health challenges.

Enhancing public transport in Rural areas: Our findings show that the travel behavior of individuals living in Rural areas is most significantly impacted by epidemiological indicators and weather conditions, primarily due to the lack of a robust public transport system. Given the limited public transport options, rural residents who are aware of the risks associated with COVID might opt to reduce their trips. In addition, the roads in rural areas may need to be more well-maintained or resilient to extreme weather conditions as in urban areas. As a result, adverse weather has a more significant impact on the feasibility and safety of travel. Investing in the development of an efficient and accessible public transport system in Rural areas is crucial for enhancing travel resilience and preparedness for future pandemics. The findings highlight the challenges unique to rural communities, and thus it is necessary to enhance connectivity, accessibility, and convenience for rural residents by exploring flexible and multi-modal solutions.

Enhancing cross-border travel and community engagement: Our findings reveal that out-of-county trips are influenced by epidemiological indicators and weather conditions, with rural residents being the most affected. Policymakers should focus on fostering collaboration with neighboring counties to ensure coordinated responses to cross-border travel challenges. Stakeholders including residents, community organizations should be involved in planning and decision-making to ensure that transport solutions align with the unique needs and preferences of rural communities. By fostering a more robust and adaptable transport system, the local communities, whether urban or rural, the travel behavior resilience of both residents and visitors from broader communities will be better equipped to navigate future pandemics.

6. Conclusion

In this study, we propose an analytical framework incorporating time-series prediction, causal impact inferring, and regression modelling. We first infer the impact of COVID vaccination intervention on the resilience in five types of travel behavior (WFH%, work/nonwork trips, out-of-county trips%, travel miles), considering the covariates, such as epidemiological indicators and weather conditions, across Metropolitan, Micropolitan, and Rural areas. We then develop PLSR models to accurately estimate the impact of vaccination rates, epidemiological indicators, and weather conditions on five types of travel behavior across three areas, during the recovery period of the pandemic. The results of BSTS models show that vaccination intervention can help to build the resilience in five types of travel behavior, especially in Rural areas. The impact of vaccination on travel behaviors presents disparities between urban and rural areas, highlighting the importance of fostering travel behavior resilience through adaptive and equitable transportation planning. PLSR model results reveal that higher COVID-19 incidence rates correlate with increased WFH%, while rising vaccination and death rates are linked to reduced WFH%, and individuals in rural areas are more sensitive to these COVID-19 indicators. Moreover, increased vaccination rates promote work and nonwork trips, whereas higher death rates notably suppress both trips, especially in Micropolitan and Rural areas. In metropolitan and micropolitan areas, higher COVID testing rates are associated with increased work and nonwork trips, while in rural areas, increased testing rates correlate with a decrease in such trips. COVID incidence rates, vaccination rates, and testing rates influence out-of-county trips%, with the most significant impact observed among rural residents. Weather conditions have an obvious impact on out-of-county trips% in Rural and Micropolitan areas but have little impact in Metropolitan areas. The COVID incidence rates have a negative impact on travel miles in Micropolitan areas, while having a positive impact on travel miles in Rural areas. Weather conditions exert varying impacts on travel miles across the three areas, with Rural areas being the least influenced.

Our findings provide policy implications on how vaccination intervention will impact travel behavior resilience and guide policymakers in implementing appropriate measures to promote economic and mobility resilience, bridge the gaps in healthcare resources, transportation infrastructure, and identify the socio-economic factors between Metropolitan and Rural areas to ensure an equitable and resilient transportation system and efficient disease containment in future pandemics. One of the limitations of this study is its reliance on mobile device datasets with potential inherent biases. Another limitation is that the dataset is restricted to a specific timeframe, not being updated beyond 20 April 2021, and this cut-off does not allow us to capture longer trends or shifts in behavior as societies further adapt. Future research could incorporate multi-modal data sources, e.g., by combining mobile device data with other travel or location tracking methods, such as smart card or vehicle tracking systems, to offer a more comprehensive view of travel patterns. Future studies should aim to access and analyze data beyond this cut-off point, and it is valuable to observe the impact of vaccinations on travel behavior resilience as more time elapses after widespread vaccination campaigns.

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