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Influencing Mechanism Analysis of Holiday Activity–Travel Patterns on Transportation Energy Consumption and Emissions in China

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Abstract: Energy shortage and atmospheric pollution problems are getting more serious in China, and transportation is the main source of energy consumption, pollutants, and carbon emissions. This study combined the activity-based analysis method with emission models, and investigated the influence mechanism of people's activity travel scheduling on transportation energy consumption and emissions on holidays. Based on the holiday travel behavior survey data, the multinomial logistic regression model was first applied to explore the decision mechanisms of individual travel-mode choices in holidays. Next, the emission model was integrated with an activity-based travel demand model to calculate and compare transportation energy consumption and emissions under different policy scenarios. The results showed that socio-demographic characteristics had significant effects on holiday activity–travel patterns, and combined mode chains had a larger number of activity points than single mode chains. With an increase in the trip time of cars, and decrease of travel distance and the number of activity points, transportation energy consumption and emissions could be reduced greatly with an adjustment of holiday activity–travel patterns. The reduced portion is mainly attracted by slow traffic and public transport. However, the effects of a single policy strategy are very limited, thus portfolio policies need to be considered by policy makers.

Keywords: energy consumption; carbon and pollutant emissions; multinomial logistic regression model; emission model; activity-travel pattern; China

1. Introduction

In China, energy consumption and pollutant emissions have increased annually with rapid urbanization, which has had a great impact on the global ecological environment and people's living conditions. At the beginning of 2013, Eastern China experienced a massive smog outbreak, affecting around 800 million people and covered 1.43 million square kilometers. As a result, PM2.5 particles reached a level of "hazardous" for many cities [1]. As the bad atmospheric environment sparked reflections for future development, the Chinese government and policy makers have paid more attention to energy conservation and emissions reduction. According to the National Plan on Climate Change (2014–2020), by 2020 the carbon emissions for one unit of GDP should be reduced by 40–45% (compared to 2005), and non-fossil energy consumption should account for around 15% of the primary energy consumption [2].

Transportation, with its high-energy consumption and emissions intensity, has become the main source of air pollution in the metropolis [3]. For example, Beijing had more than 20 million permanent residents with a total of 5.6 million vehicles in 2013. The energy consumption for transportation is 19 million tons of standard coal per year, accounting for 27% of the total energy consumption, and 31.1%

of the total pollutant emissions of the city. Therefore, reducing energy consumption and emissions from transportation is of great significance for atmospheric pollution control in the metropolis [4].

Energy consumption and pollutant emissions vary greatly for different travel-modes; energy consumption for cars is 1.08 tons of standard coal, which is 12 times that of rail transit, and 5 times that of buses. The HC and CO emissions of cars are 10–20 times that of buses for every 10,000 kilometers. However, in reviewing the travel patterns of Beijing over the last decade, the proportion of car travel continues to grow, while the proportion of bicycle travel shrinks every year. From 2005 to 2013, the proportion of car travel increased from 29.8% to 32.7%, while the proportion of bicycle travel decreased from 30.3% to 12.1%. Furthermore, some data showed that if the main travel-mode in Beijing shifted to rail transit (like Tokyo), energy consumption, NO_x, and carbon emissions could be reduced by 10, 51, and 10%, respectively. If the main travel-mode shifted to cycling (like Copenhagen), energy consumption, NO_x, and carbon emissions would decrease by 18, 49, and 18%, respectively [5]. Therefore, optimizing urban travel patterns is an important measure to reduce energy consumption and carbon emissions in the metropolis.

Urban travel patterns are generated from people's daily travel and activities, and travel behavior analysis is the basis for analyzing urban travel patterns requiring low energy and emissions. There are many influencing factors for individual travel-mode choices that further affect energy consumption and carbon emissions in the metropolis, such as travel speed, travel time, travel distance, and so on [6]. However, most of these factors are travel-related, and the activity scheduling effects on transportation energy consumption and emissions have been seldom investigated. Therefore, this study applied the activity-based method to analyze the relationship between activity travel scheduling, transportation energy consumption, and emissions in Beijing.

The holiday period is a good time for people to go out and enjoy their spare time, and the holiday economy effectively stimulates the growth of national consumption and demands of tourism, leisure, and recreation. However, holiday travel demands often exceed the service capability of the infrastructure, which leads to a series of traffic problems including travel delays, traffic accidents, and traffic congestions [7]. Holiday traffic pollution also becomes more serious during this time. Therefore, this study used holiday activity travel scheduling as the study object, and investigated the relationship between activity-travel patterns and transportation energy consumption and emissions during the holidays. By integrating the activity-based travel demand model with the emission models, effective implementation methods were obtained by calculating and comparing transportation energy consumption and emissions under different policy scenarios.

This study is organized as follows. Section 2 briefly reviews the literature on transportation energy consumption and emissions research, as well as related travel behavior analysis and emission factor models. It also indicates the lack of existing research and clarifies the contribution of this study. Section 3 describes the modeling approaches and explains the meaning of the variables used in the models. Section 4 contains the data and survey, and a discussion of the model results is presented in Section 5. Finally, the important findings and recommendations are summarized in Section 6.

2. Literature Review

As global energy shortages and environmental degradation are becoming more serious, energy conservation and emissions reduction has become a new direction in city development [8]. The abatement efforts in energy consumption and emissions have been discussed from various aspects including regional allocation [9], demographic distribution [10,11], energy technology [12,13], and many others. This study focuses on transportation energy consumption and emissions, as transportation is the largest emitter of greenhouse gases (GHGs) and the main cause of air pollution in cities [14,15]. Pollutant emissions mainly consist of HC, CO, NO_x PM, etc. Carbon dioxide (CO_2) is the main component of greenhouse gases (GHGs), and terms such as 'carbon footprint' or 'carbon emission' have become tremendously popular over the last few years [16]. Furthermore, these are important indicators to measure the development of sustainable transport.

Research on transportation energy consumption and emissions covers several areas of interest: environmental influence, urban travel patterns, lifestyle, and policy analysis [17–20]. Hankey [21] and Marshall and Pan [22] indicated that comprehensive compact development was better for reducing GHG emissions, and that multi-modal transport was an inevitable trend of future urban development. Chapman [17] demonstrated ways to reduce carbon emissions in the transport sector from three aspects: car use, road freight, and aviation. Additionally, some research has focused on the development of new energy vehicles, such as hybrid electric vehicles (HEV), battery electric vehicles (BEV), and fuel cell electric vehicles (FCEV). Thiel et al. [23] and Ou et al. [24] investigated the effects of new energy vehicles on greenhouse gas emissions under different new energy policy scenarios.

One method to break the dependence on petroleum is to apply new technologies for alternative transport fuels to reduce traffic-related emissions. However, short-term behavioral change is more crucial as long-term technological solutions are yet to be fully realized [25]. Many studies have attempted to analyze the effect of travel patterns and transportation system design on traveler behavior and thereby on transport emissions [26,27]. Related research can be divided into macro travel pattern analysis and micro individual travel-mode choices.

On a macro level, reasonable urban travel patterns have been investigated from an optimization perspective, and consider the constraints of the social economy, resources, and environment [28–30]. Xie [31] analyzed the internal and external influencing factors for the evolution of an urban passenger transportation system, and the ecological urban passenger traffic structure was obtained using a system dynamics method. Long [32] provided rules for urban traffic structure optimization, and built a multi-objective optimization model under the low carbon city target. As econometric model has been introduced into the transportation field, the disaggregate model has been widely used in the analysis of travel-mode choices. Trip (or tour related characteristics), socio-demographic characteristics, personal preferences, built environment, and land use are all essential influencing factors [33–36]. However, most of these studies have only focused on individual utility maximization, and analyzed the influencing mechanisms of travel-mode choices from the micro level. Social benefit or system utility such as urban transportation efficiency and urban carbon emissions have seldom been considered in these studies; therefore, the combination of the micro model with the macro targets is an innovation in urban travel pattern research.

Moreover, there are all kinds of emission factor models to measure vehicle emissions, including the MOBILE model, COPERT model, International Vehicle Emission (IVE) model, and CMEM model [37,38]. Among them, the MOBILE model was the earliest and most widely used model in China, and many cities have applied this model to establish their local emission inventories. The IVE model was first applied in Beijing and Shanghai in 2004, and some universities have conducted research into the application of the IVE model [39–41]. However, emission models are mainly used in macro studies, which heavily relies on temporal or spatial aggregation, which means that micro individual behavior is difficult to consider with these models.

To fill this knowledge gap, some scholars have integrated the activity-based travel demand model with emission models, therefore controlling the influence of land use and other factors [42–45]. However, most efforts focus on light-duty vehicles, and multi-modal transport is seldom considered. In reality, most studies only apply a priority ordering scheme to define the travel-mode of activity travel scheduling to reduce the research complexity, even in activity-based travel behavior research [46–48]. Thus, the combined travel-mode of the travel-mode chain for activity travel scheduling is seldom investigated. Moreover, most studies take commuting as the research objective, and research focusing on holiday travel behavior is rare and limited.

To overcome the limitations of previous research, our study makes the following incremental contributions to the field. First, by combining the activity-based travel demand model with the emission factor model, we can improve the forecasting accuracy of holiday transportation energy consumption and emissions under different policy scenarios. Second, by analyzing the travel-mode chain choices under a multimodal transport network, this will provide more insights into understanding the influencing mechanisms of potential transportation actions. Third, this research will provide empirical support for the development of holiday travel demand management policies, based on the activity analysis.

3. Methodology

3.1. Activity-Based Travel Demand Model

The traditional trip-based model has many problems as it treats every trip in an isolated manner and does not account for the relationship between different trips for travel. To counter this, an activity-based model was provided which used activity travel scheduling as the study object. Activity travel scheduling is defined as a set of tours or trip chains tied together in one-day travel, and a tour refers to a chain of trips starting and ending at home [34,49]. The components of the activity travel scheduling not only include different activities, but also include a series of trips derived from the activities. Thus, there are a lot of spatiotemporal, structural, and activity information which interrelate and interact with each other.

The travel behavior decision process involves multiple facets or portfolio choices for travelers to fulfil their travel needs. The travel behavior characteristics are divided into travel and activity characteristics, including travel time, travel distance, travel-mode, activity location, activity duration, etc. These characteristics are statistics of tour or scheduling, instead of trips, and they interrelate and interact with each other. Moreover, the influencing factors for travel behavior choices cover all kinds of aspects, such as personal preferences, socio-demographic characteristics, built environment, travel information, and so on [50–53].

As different travel-modes have different transportation energy consumption and pollutant emissions, this study focused on the travel-mode chain choices in holidays. As one activity travel scheduling may involve more than one trip mode, the travel-mode chain consists of a set of trip modes tied together in the one-day scheduling. In this study, taxis were classified as cars, as these two travel-modes are very similar in transportation energy consumption and emissions within city areas. Walking and cycling were all classified as slow traffic as their transportation energy consumption and emissions are all equal to zero. Therefore, the type of travel-mode chains included slow traffic (i.e., foot or bike), bus chain, subway chain, car chain (including taxi), bus–subway chain, bus–car chain, subway–car chain, and bus–subway–car chain. Among them, the bus–car chain, subway–car chain, and bus–subway–car chain belong to a new kind of travel-mode called Park and Ride (P&R). Moreover, these travel-mode chains were divided into a single mode chain and a combined mode chain. Single mode chain represents the use of one kind of trip mode in the daily activity travel scheduling, while the combined mode chain consists of two or more kinds of trip modes.

The choice set of travel-mode chains has eight discrete outcomes, so this study used the multinomial logistic regression model to predict the probabilities for different travel-mode chains. In economics, the multinomial logistic regression model is one type of discrete choice model to describe, explain, and predict choices between different discrete alternatives [54]. There are many kinds of discrete choice models, considering choice alternatives, interpersonal heterogeneity, intra-individual choice dynamics, and heterogeneous choice. As the activity travel scheduling survey used a revealed preference (RP) survey, it could only obtain people's actual activity and travel situation during the holidays, and not the attributes of the other alternatives. Moreover, some advanced logit models, such as the mixed logit model, are difficult for forecasting analysis. Thus, the multinomial logistic regression model was the most suitable for the data and could meet the study purpose.

Suppose that there are k categorical outcomes, and let the base outcome be 1. Generally, any alternative can be the base outcome. The probability that the response or observation n chooses the alternative i is:

$$P_{ni} = \Pr(y_n = i) = \begin{cases} \frac{1}{1+\sum\limits_{i=2}^{k} \exp(x_n\beta_i)}, & \text{if} \quad i = 1 \\ \frac{\exp(x_n\beta_j)}{1+\sum\limits_{i=2}^{k} \exp(x_n\beta_i)}, & \text{if} \quad i > 1 \end{cases} \tag{1}$$

where x_n is the observed values of the independent variables for the observation n, and β_i is the coefficient of alternative i The log pseudo likelihood is:

$$\ln L = \sum_n w_n \sum_{i=1}^{k} I_i(y_n) \ln P_{ni} \tag{2}$$

where w_n is an optional weight and:

$$I_i(y_n) = \begin{cases} 1, & \text{if } y_n = i \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

The parameters were estimated via the Newton–Raphson maximum likelihood estimation [54]. The likelihood-ratio test was used to estimate the overall significance of the model, with a value of 0 indicating an overall significant model [55]. Moreover, ρ^2 is another good indicator of fit to evaluate model performance. A higher value of ρ^2 indicates a better model fit. In practice, a value between 0.2 and 0.4 is considered as a good model fit [56,57].

3.2. Integration with Emission Estimation Method

Transportation emissions can be divided into pollutant emissions and GHGs emissions. Pollutant emissions mainly include HC, CO, NO_x PM, etc. GHGs emissions include CO_2, CH_4, N_2O, and others. Different emissions have different emission factors, and the estimation methods are slightly different for these two types of emissions.

3.2.1. Pollutant Emission Model

The estimation of pollutant emissions focused on the vehicle kilometers of travel (VKT) and pollutant emission factors [58]. VKT is the total miles (kilometers) traveled by all vehicles, which is calculated by the number of vehicles times the miles (kilometers) traveled. It can be transformed into revenue passenger mile (RPM), which is the total miles (kilometers) traveled by the travelers. Suppose there are N travelers, N_j is the total number of vehicles for trip mode j; PC_j and LF_j represent the rated passenger capacity and load factor of trip mode j, respectively. Let EF_{jp} be the emission factor of pollutant p and trip mode j. Then, the estimation for pth pollutant emission E_p is denoted as:

$$E_p = \sum_j N_j \times VKT_j \times EF_{jp} = \sum_j \frac{RPM_j}{PC_j \times LF_j} \times EF_{jp} \tag{4}$$

RPM is relative with modal split and personal travel distance. Let D_{nj} be the travel distance of individual n with trip mode j; P_j is the modal split, and AT_j is the average travel distance of the travelers with trip mode j. Then, the RPM_j can be expressed as:

$$RPM_j = \sum_n D_{nj} = N \times P_j \times AT_j \tag{5}$$

Moreover, this study takes the activity travel scheduling as the study object, which consists of a set of trip modes. The RPM of trip mode j comes from different travel-mode chains. Let $P_i = \frac{1}{N}\sum\limits_n P_{ni}$, and AT_{ij} is the average travel distance of travel-mode chain i and trip mode j. Then, Equation (5) can be expressed as:

$$RPM_i = \sum_i N \times P_i \times AT_{ij} = \sum_i \sum_n P_{ni} \times AT_{ij} \tag{6}$$

The emission formula can build a relationship with the probability of travel-mode chain choice by taking Equation (6) into Equation (4), the estimation for pth pollutant emission E_p can be expressed as:

$$E_p = \sum_n \sum_i \sum_j P_{ni} \times AT_{ij} \times \frac{EF_{jp}}{PC_j \times LF_j} \tag{7}$$

3.2.2. Carbon Emission Model

Carbon emission is the general term used for greenhouse gas emissions, and CO_2 is the main component of GHGs; therefore, this study only calculated the CO_2 emissions. The estimation method relies on the fuel combustion activity FC_a and the default CO_2 emission factor EF_a. a refers to the type of fuel, such as motor gasoline, diesel oil, liquefied petroleum gases, etc. The approach is represented in Equation (8).

$$E_{CO_2} = \sum_a FC_a \times EF_a \tag{8}$$

Activity data may be provided either by fuel consumption (taken to be equal to the fuel sold within the country), or by vehicle kilometers travelled (VKT). As the fuel sold data collected nationally is difficult to obtain, it is good practice to estimate fuel use from the distance travelled data. Therefore, the estimation method of FC_a is similar to the pollutant emission model, except the pollutant emission factor EF_{jp} becomes the energy consumption factor CF_{ja}. Moreover, fuel type is considered in the estimation formula. Suppose that each type of trip mode only uses one type of fuel, a can be replaced by j, and the equation for estimating FC_a may be expressed as:

$$FC_j = \sum_j N_j \times VKT_j \times CF_j \tag{9}$$

Then, the CO_2 emission Equation (8) turns into:

$$E_{CO_2} = \sum_j N_j \times VKT_j \times CF_j \times EF_j \tag{10}$$

Here we also utilize the RPM to build the relationship between the carbon emission model and the activity-based travel demand mode, where the research thinking is the same as the estimation method of pollutant emission model. Therefore, the estimation for CO_2 emission can be expressed as:

$$E_{CO_2} = \sum_n \sum_i \sum_j P_{ni} \times AT_{ij} \times \frac{CF_j}{PC_j \times LF_j} \times EF_j \tag{11}$$

It should be noted that when the emission factor is divided by the number of passengers, the factor unit changes from grams per kilometer (g/km) to grams per passenger and kilometer (g/p.km). The same goes for the energy consumption factors. The new factors obtain more accurate information, and their values provided a modal shift direction for saving transportation energy and reducing pollutants and carbon emissions. This study used this new factor as the default factor, and the data of the other variables were obtained from the survey.

3.3. Default Factors and Model Variables

The data used for the pollutant emission and energy consumption factors were obtained from the results of Wang [5], which were calculated based on the actual situation of Beijing. Taxis were classified as cars due to their similar energy consumption and pollutant emissions, so our study took advantage of their average value as the car data. The default factors are shown in Tables 1 and 2.

Table 1. Transportation default pollutant emission factors for different trip modes (g/p.km).

Trip Mode	Bus	Subway	Car	Slow Traffic
CO Emission Factor	1.62	0.12	17.65	0
NO_x mission Factor	0.26	0.02	0.86	0

Table 2. Transportation default energy consumption factor for different trip modes (MJ/p.km).

Trip Mode	Bus	Subway	Car	Slow Traffic
Energy Consumption Factor	0.714	0.322	3.2	0

Furthermore, different trip modes have different CO_2 emissions based on the type of fuel. For buses and cars, this study assumed that their fuels mainly consisted of gas/diesel oil and motor gasoline, respectively. The default CO_2 emission factor data were taken from the IPCC Emission Factor Database [58]. Some studies have indicated that the IPCC default emission factors may overestimate CO_2 emissions for China [59–61]. However, there are no current official data for carbon emission factors for different trip modes in China, and there are few related studies. Therefore, this study used IPCC data as the default CO_2 emission factors for buses and cars.

For the subway, there are indirect CO_2 emissions from third parties who generate the electric power required for the operation of the subway trains. Thermal sources are predominant, with a mix of coal, oil, and gas. This study applied the baseline emission factor for the regional power grid in North China issued by the National Development and Reform Commission of Climate Change in China [62]. A baseline emission factor was calculated as a combined margin (CM), consisting of the combination of the operating margin (OM) and build margin (BM). OM relates to the grid dispatching operation, which was calculated as the generation-weighted average emissions per electricity unit (tCO_2/MWh) of all generating sources serving the system. BM relates to the power grid construction, which is the generation-weighted average emission factor (tCO_2/MWh) from a sample of power plants. The weights for OM and BM were 50% by default, so the emission factor for the subway was the weighted average of OM and BM [63]. The unit was changed from carbon emissions per megawatt hour (tCO_2/MWh) to carbon emissions per terajoule ($kgCO_2$/TJ) and the results are shown in Table 3.

Table 3. Transportation default CO_2 emission factor for different trip modes ($kgCO_2$/TJ).

Trip Mode	Bus	Subway	Car	Slow Traffic
Fuel Type	Gas/Diesel Oil	Coal, Oil and Gas	Motor Gasoline	Bioenergy
CO_2 Emission Factor	74,100	211,000	69,300	0

It was found that the CO_2 emission factor for the subway was much higher than the other trip modes, as the main form of electricity generation in China is thermal power, and the amount of coal used in the north is higher than that of the south. For slow traffic, which only spent bioenergy to generate kinetic energy, there were no CO_2 emissions.

Based on the above analysis, the model variables used in this study are presented in Table 4. This study selected the travel-mode chain, and pollutant and carbon emissions as the dependent variables. The independent variables included socio-demographic characteristics, travel characteristics, activity characteristics, and trip characteristics.

Table 4. Definition of variables.

Variable Category	Variable Name (Unit)	Description	Type
		Dependent variables	
Tour structural characteristics	Travel-mode chain	Type of travel-mode chain	Categorical: 1 = slow traffic; 3 = bus chain; 4 = subway chain; 5 = car chain; 34 = bus–subway chain; 35 = bus–car chain; 45 = subway–car chain; 345 = bus–subway–car chain
Pollutant and carbon emissions	CO emissions (g)	Pollutant emissions	Continuous
	NO_x emissions (g)	Pollutant emissions	Continuous
	CO_2 emissions (g)	Carbon emissions	Continuous
		Independent variables	
Socio- demographic characteristics	Gender	Gender	Binary: 0 = Male; 1 = Female
	Age	Age	≥18 integers
	Pincome (ten thousand RMB)	Personal monthly income	Continuous
Travel characteristic	Accessibility (km)	Distance from home to the nearest stop, station or parking lot	Continuous
	Travel time (h)	Total travel time for a tour	Continuous
	Travel distance (km)	Total travel distance for a tour	Continuous
Activity characteristics	Activity location	Survey location	Binary: 0 = Xidan; 1 = The Summer Palace
	Activity points	Number of activity locations for a tour	≥1 integers
Trip characteristic	Trip mode	Type of trip mode	Categorical: 1 = Walk; 2 = Bike; 3 = Bus; 4 = Subway; 5 = Car
	Trip time (min)	Travel time for a trip	Continuous
	Trip distance (km)	Travel distance for a trip	Continuous
	Trip speed (km/h)	Travel speed for a trip	Continuous

4. Survey and Data

The activity-based survey was conducted in Xidan and the Summer Palace during Tomb-Sweeping Day (2–4 April), 2012. Xidan, in Beijing, is a prosperous commercial street, and the Summer Palace is one of the most famous imperial gardens, with a large number of tourists. These two sites have strong representativeness among holiday attractions. The Tomb-Sweeping Day holiday usually lasts for three days, when people often have an outing in Spring. The respondents were mainly Chinese citizens, aged 18 years and older. The survey applied a postal survey combined with a face-to-face interview, and 1688 questionnaires were distributed and 415 effective samples obtained.

The questionnaire recorded the traveller's one-day travel diary during the holidays, including the traveller's socio-demographic characteristics, trip characteristics, travel characteristics, and activity characteristics. Related indicators and explanations are shown in Table 4, and the descriptive statistical analysis results for these indicators over different travel-mode chains are shown in Tables 5–8.

For the socio-demographic characteristics, there was a roughly equal proportion of men and women over different travel-mode chains. People aged over 50 years old seldom used cars or a combined mode as their travel-mode during the holidays, which correlated with their physical strength. Moreover, personal monthly income was mainly between 2000–4000 RMB for people choosing slow traffic, bus chain, and subway chain in the holidays, while car travellers had higher incomes. Among the travellers choosing the bus–subway chains, about one-third (30.88%) were students without income.

For the activity characteristics, the travellers in Xidan and the travellers at the Summer Palace in the holidays showed an inclination towards the bus chain and car chain, respectively. In addition, travellers in Xidan preferred to choose the subway chain or a combined mode as their activity-travel pattern. Regarding the number of activity points, the combined mode chains had more activity points than the single mode chains, which reflected the structural complexity of holiday tours from another point of view.

Table 5. Frequency distribution of socio-demographic characteristics over different travel-mode chains.

Variable	Category	Travel-Mode Chain															
		1		3		4		5		34		35		45		345	
		N	%	N	%	N	%	N	%	N	%	N	%	N	%	N	%
Gender	Male	2	33.33	35	45.45	59	50.43	12	48	61	44.85	3	42.86	5	45.45	9	52.94
	Female	4	66.67	42	54.55	58	49.57	13	52	75	55.15	4	57.14	6	54.55	8	47.06
Age	18–20	1	16.67	7	9.090	24	20.51	1	4	24	17.65	0	0	1	9.090	6	35.29
	21–30	1	16.67	45	58.44	71	60.68	13	52	92	67.65	3	42.86	8	72.73	9	52.94
	31–40	1	16.67	14	18.18	12	10.26	7	28	14	10.29	2	28.57	2	18.18	2	11.76
	41–50	2	33.33	5	6.490	7	5.980	4	16	6	4.410	1	14.29	0	0	0	0
	51–60	0	0	1	1.300	1	0.850	0	0	0	0	0	0	0	0	0	0
	$\geq$ 61	1	16.67	5	6.490	2	1.710	0	0	0	0	1	14.29	0	0	0	0
Pincome (RMB)	0	1	16.67	13	16.88	24	20.51	1	4	42	30.88	1	14.29	1	9.090	7	41.18
	$\leq$ 500	1	16.67	4	5.190	3	2.560	0	0	4	2.940	0	0	0	0	2	11.76
	501–2000	1	16.67	12	15.58	21	17.95	4	16	24	17.65	0	0	2	18.18	1	5.880
	2001–4000	2	33.33	27	35.06	31	26.50	5	20	35	25.74	1	14.29	1	9.090	3	17.65
	4001–6000	0	0	15	19.48	20	17.09	4	16	23	16.91	3	42.86	4	36.36	2	11.76
	6001–8000	1	16.67	5	6.490	13	11.11	4	16	3	2.210	0	0	2	18.18	1	5.880
	$\geq$ 8000	0	0	1	1.300	5	4.270	7	28	5	3.680	2	28.57	1	9.090	1	5.880
Each Total		6	1.52	77	19.44	117	29.55	25	6.31	136	34.34	7	1.77	11	2.78	17	4.29

Table 6. Frequency distribution of activity characteristics over different travel-mode chains.

Variable	Category	Travel-Mode Chain															
		1		3		4		5		34		35		45		345	
		N	%	N	%	N	%	N	%	N	%	N	%	N	%	N	%
Activity location	Xidan	2	33.33	31	40.26	63	53.85	11	44	76	55.88	3	42.86	6	54.55	13	76.47
	The Summer Palace	4	66.67	46	59.74	54	46.15	14	56	60	44.12	4	57.14	5	45.45	4	23.53
Activity points	1	6	100	59	76.62	98	83.76	16	64	70	51.47	2	28.57	6	54.55	5	29.41
	2	0	0	14	18.18	15	12.82	7	28	44	32.35	3	42.86	4	36.36	6	35.29
	3	0	0	3	3.900	3	2.560	2	8	19	13.97	1	14.29	1	9.090	6	35.29
	4	0	0	1	1.300	1	0.850	0	0	3	2.210	1	14.29	0	0	0	0
Each Total		6	1.52	77	19.44	117	29.55	25	6.31	136	34.34	7	1.77	11	2.78	17	4.29

Table 7. Summary results of travel characteristics over different travel-mode chains.

Travel-Mode	Variable (Unit)	Obs	Mean	Std. Dev.	Min	Max
1	Accessibility (km)	6	0.83	0.379	0.33	1.2
	Travel time (h)	6	0.681	0.226	0.333	1
	Travel distance (km)	6	5.583	6.312	1	18
3	Accessibility (km)	77	0.599	0.431	0.100	2.500
	Travel time (h)	77	2.135	1.094	0.500	4.833
	Travel distance (km)	77	29.66	25.52	5.500	158
4	Accessibility (km)	117	0.746	0.460	0.300	2
	Travel time (h)	117	2.027	1.012	0.500	6.333
	Travel distance (km)	117	35.14	22.99	6	143.1
5	Accessibility (km)	25	0.299	0.219	0.100	0.950
	Travel time (h)	25	1.499	0.791	0.500	3.583
	Travel distance (km)	25	42.74	30.65	9	135
34	Accessibility (km)	136	0.599	0.406	0.200	2
	Travel time (h)	136	2.719	1.066	0.917	7
	Travel distance (km)	136	46.62	27.07	8.500	139
35	Accessibility (km)	7	0.589	0.331	0.270	1.200
	Travel time (h)	7	1.762	1.187	0.833	4.083
	Travel distance (km)	7	30.26	14.61	12	54.20
45	Accessibility (km)	11	0.683	0.455	0.300	1.800
	Travel time (h)	11	2.053	0.604	1.167	3.500
	Travel distance (km)	11	45.64	28.03	12	108
345	Accessibility (km)	17	0.485	0.212	0.270	1
	Travel time (h)	17	2.533	1.020	1.333	5.250
	Travel distance (km)	17	44.94	22.69	14.30	103.6

Table 8. Frequency distribution of trip characteristics over different travel-mode chains.

Travel-Mode	Trip Mode														
	1			**2**			**3**			**4**			**5**		
	Trip Time (min)	**Trip Distance (km)**	**Trip Speed (km/h)**	**Trip Time (min)**	**Trip Distance (km)**	**Trip Speed (km/h)**	**Trip Time (min)**	**Trip Distance (km)**	**Trip Speed (km/h)**	**Trip Time (min)**	**Trip Distance (km)**	**Trip Speed (km/h)**	**Trip Time (min)**	**Trip Distance (km)**	**Trip Speed (km/h)**
1	26.67	2.00	4.50	50.00	9.17	11.00									
3							104.44	28.22	16.21						
4										89.84	35.30	23.58			
5													118.04	88.30	44.88
34							61.28	15.89	15.56	70.99	29.64	25.05			
35							45.71	14.23	18.68				22.57	15.43	41.02
45										65.83	34.14	31.12	25.17	11.33	27.01
345							35.63	10.62	17.88	46.55	28.96	37.33	33.79	13.28	23.58

For the travel characteristics, the combined mode chains had longer travel time and travel distance, which were related to the number of activity points. The bus chain and subway chain had a longer travel time with a shorter travel distance, while the car chain had a longer travel distance with shorter travel time. Moreover, the close accessibility was more convenience for car travellers.

For the trip characteristics, the car was the fastest trip mode in the holidays. However, car speed decreased significantly, even lower than subway speed within the P&R chains, which may be a reason for travellers choosing P&R during this period. It should be noted that the trip time and trip distance did not consider the transfer time and transfer distance inside.

5. Results and Analysis

5.1. Activity-Based Travel Demand Model Analysis

To investigate the internal influence mechanism of the travel-mode chain choices and explore effective ways to reduce energy consumption, pollutants and carbon emissions in a metropolis, a multinomial logistic regression model was built based on the activity analysis method. The model parameters were estimated by the software Stata using the Newton–Raphson maximum likelihood estimation method. The model results are shown in Table 9. The p-value = 0, indicating that the model was significant overall. The value of ρ^2 is 0.2138, which can be considered as a good fit.

It should be noted that the coefficients from the multinomial logistic model are difficult to interpret as they are relative to the base outcome. Another method used to evaluate the effect of covariates was to examine the marginal effect of changing their values on the probability of observing an outcome. This study interpreted the model results using average marginal effects for each outcome over the estimation sample (Table 10).

For the socio-demographic characteristics, if people's monthly income increased by 10,000 RMB, the probability had a 10.1% points increase in choosing the car chain as their activity-travel pattern in the holidays. At the same time, the probability for choosing the bus-subway chain and subway–car chain decreased by 18.4% points and increased 4.8% points, respectively. That indicated that people were willing to choose comfortable and convenient travel-modes in the holidays when their income increased.

For the activity characteristics, compared with the travellers in Xidan, the travellers in the Summer Palace preferred the bus chain in the holidays. If their destinations included Xidan, the chances of selecting the bus–subway chain and bus–subway–car chains increased by 10.8% points and 6% points, respectively. For every one unit increase of the number of activity points, the probability for choosing slow traffic, bus chain and subway chains decreased by 7.9, 2.5, and 10.5%, respectively. Furthermore, the probability increased for choosing the car chain, bus–subway chain, bus–car chain, and bus–subway–car chain at the same time. That meant that combined mode chains have more activity points than single mode chains, which was consistent with the descriptive statistical analysis results.

For the travel characteristics, the probability of selecting the car chain dropped fastest when the access distance to the nearest stop, station, or parking lot increased. However, an increase of one kilometer of accessibility increased the subway chain choice probability by 25.9% points, which meant that the attraction of the subway chain was larger than the other activity-travel patterns during the holidays, when walking time cost increased. For a one hour decrease in travel time in the holidays, the probability of choosing the car and bus chains increased by 9.3%, and decreased by 7.3%, respectively. However, the probability decreased for the bus–subway chain and increased for P&R when travel time decreased. Moreover, extending the travel distance increased the choice probability of the car and subway–car chains in the holidays. The choice probability of the slow traffic and bus chain decreased with an increase in travel distance.

Table 9. Parameter estimates and their significance.

Variable	Travel-Mode Chain							
	1	**3**	**4**	**5**	**34**	**35**	**45**	**345**
Pincome	−0.675	0.519	0.989 **	3.715 ***		3.365 **	2.688 ***	−0.389
	(2.321)	(0.519)	(0.497)	(0.916)		(1.575)	(1.033)	(1.254)
1. Activity location	2.469 ***	1.323 ***	0.559 *	0.504		0.363	−0.007	−1.371 *
	(0.784)	(0.314)	(0.296)	(0.642)		(1.116)	(0.716)	(0.705)
Accessibility	1.646 *	0.026	0.855 ***	−9.601 **		0.210	0.726	−1.069
	(0.885)	(0.425)	(0.309)	(3.931)		(1.109)	(0.736)	(0.925)
Travel time	−3.022 **	0.041	−0.463 **	−3.071 ***		−1.204	−1.070 ***	−0.418
	(1.532)	(0.202)	(0.216)	(0.816)		(1.244)	(0.349)	(0.272)
Travel distance	−0.380	−0.037 ***	−0.003	0.066 ***		−0.001	0.025 **	0.009
	(0.292)	(0.014)	(0.008)	(0.020)		(0.037)	(0.012)	(0.009)
Activity points	−10.534 ***	−0.717 ***	−0.923 ***	0.325		0.815 *	0.086	0.875 ***
	(1.321)	(0.261)	(0.269)	(0.390)		(0.426)	(0.505)	(0.308)
Constant	13.898 ***	0.890	1.192 **	2.768 **		−3.628 *	−2.845 ***	−1.874
Observations	396	396	396	396	396	396	396	396
Prob > chi2 = 0.0000								
ρ^2 = 0.2138								

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 10. Marginal effects of different variables for each travel-mode chain.

Variable	Travel-Mode	Delta-Method					
		dy/dx	**Std.Err.**	**z**	***P* > |z|**	**[95% Conf. Interval]**	
Pincome							
	1	−0.012	0.020	−0.620	0.533	−0.051	0.026
	3	−0.029	0.059	−0.490	0.625	−0.145	0.087
	4	0.075	0.072	1.040	0.298	−0.066	0.217
	5	0.101 ***	0.028	3.570	0.000	0.046	0.157
	34	−0.184 **	0.076	−2.410	0.016	−0.333	−0.035
	35	0.039	0.028	1.370	0.170	−0.017	0.094
	45	0.048 *	0.025	1.940	0.053	−0.001	0.097
	345	−0.039	0.046	−0.850	0.395	−0.129	0.051
1. Activity location							
	1	0.014	0.009	1.500	0.134	−0.004	0.032
	3	0.152 ***	0.038	3.990	0.000	0.077	0.226
	4	0.010	0.044	0.230	0.822	−0.077	0.096
	5	0.003	0.020	0.150	0.880	−0.036	0.042
	34	−0.108 **	0.044	−2.430	0.015	−0.195	−0.021
	35	0.000	0.016	0.000	0.999	−0.031	0.031
	45	−0.011	0.017	−0.650	0.514	−0.043	0.022
	345	−0.060 ***	0.022	−2.720	0.007	−0.103	−0.017
Accessibility							
	1	0.013 *	0.008	1.660	0.097	−0.002	0.029
	3	0.012	0.051	0.240	0.813	−0.087	0.111
	4	0.259 ***	0.052	5.020	0.000	0.158	0.361
	5	−0.336 ***	0.085	−3.970	0.000	−0.502	−0.170
	34	0.032	0.058	0.540	0.589	−0.083	0.146
	35	0.016	0.017	0.940	0.347	−0.017	0.049
	45	0.032 *	0.017	1.900	0.057	−0.001	0.065
	345	−0.029	0.033	−0.870	0.386	−0.093	0.036
Travel time							
	1	−0.021	0.016	−1.310	0.191	−0.053	0.011
	3	0.073 ***	0.028	2.650	0.008	0.019	0.127
	4	−0.025	0.035	−0.710	0.476	−0.094	0.044
	5	−0.093 ***	0.034	−2.770	0.006	−0.159	−0.027
	34	0.095 ***	0.027	3.510	0.000	0.042	0.148
	35	−0.010	0.019	−0.540	0.592	−0.047	0.027
	45	−0.015 *	0.009	−1.710	0.087	−0.033	0.002
	345	−0.003	0.009	−0.380	0.702	−0.021	0.014

Table 10. *Cont.*

Variable	Travel-Mode	Delta-Method					
		dy/dx	Std.Err.	z	$P > \lvert z \rvert$	[95% Conf. Interval]	
Travel distance							
	1	−0.003 **	0.001	−2.080	0.038	−0.006	0.000
	3	−0.005 ***	0.002	−2.580	0.010	−0.008	−0.001
	4	0.002	0.001	1.340	0.180	−0.001	0.005
	5	0.003 ***	0.001	3.160	0.002	0.001	0.004
	34	0.002	0.001	1.440	0.149	−0.001	0.004
	35	0.000	0.001	0.030	0.979	−0.001	0.001
	45	0.001 **	0.000	2.560	0.011	0.000	0.001
	345	0.000	0.000	1.420	0.156	0.000	0.001
Activity points							
	1	−0.079 *	0.041	−1.940	0.052	−0.158	0.001
	3	−0.025	0.036	−0.680	0.498	−0.096	0.047
	4	−0.105 **	0.046	−2.270	0.023	−0.195	−0.014
	5	0.027 **	0.012	2.220	0.026	0.003	0.050
	34	0.107 ***	0.032	3.390	0.001	0.045	0.169
	35	0.019 **	0.008	2.280	0.023	0.003	0.035
	45	0.013	0.012	1.070	0.285	−0.011	0.036
	345	0.043 ***	0.013	3.360	0.001	0.018	0.069

Note: dy/dx for factor levels is the discrete change from the base level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.2. Scenario Design and Prediction

To investigate effective ways to save vehicle fuel consumption and reduce vehicle emissions, a scenario analysis was conducted to illustrate different policy effects on people's activity-travel pattern choices, vehicle energy consumption, and emissions. Cars had a higher energy consumption and emission intensity compared to other travel-modes, therefore reducing the proportion of car trips could decrease transportation energy consumption and emissions to some extent. In the results of the travel demand model, a decrease in the number of activity points could reduce the probability of choosing the car chain, bus–subway chain, bus–car chain, and bus–subway–car chain. For an hour increase in travel time, the probability for choosing the car chain decreased by 9.3%. Shortening travel distance also decrease the probability of selecting the car and subway–car chains in the holidays. Therefore, scenarios were provided from three aspects: a decrease in travel distance, an increase in car trip time, and a limitation on the number of holiday activity points. Nine scenarios were generated by these three types of policy.

Given the limited sample size, the absolute value of energy consumption and vehicle emissions for the sample was meaningless. Instead, this study used a relative value to compare the effects of various policies with the zero-policy situation, which was chosen as the benchmark. The likelihood of each travel-mode chain was calculated by averaging the probabilities across individuals, and the energy consumption, pollutant emissions, and carbon emissions under each policy scenario were compared with the benchmark scenario. These results are shown in Tables 11–13.

As per the Work Plan for Controlling Pollution Emission (WPCPE) in Beijing (2013–2017), the Beijing municipal government made a proposal to cut 5% off the total vehicle fuel consumption and reduce vehicle emissions by 25% by the end of 2017 [64]. This study used these purposes as the criteria by which to measure the effects of each policy scenario.

Table 11 shows three scenarios under the policy of shortening travel distance in holidays—i.e., a decrease in travel distance by 5, 10, and 15%, respectively—while the other influencing factors remained the same. The results indicated that a decrease in travel distance increased the proportion of bus chains in the holidays, which was mainly transferred from the car chains. When holiday travel distance was reduced by 10%, vehicle energy consumption was reduced by 7.4%, which reached the objectives of the WPCPE in Beijing. When holiday travel distance was reduced by 15%, carbon emissions were reduced by 7.59%, CO emissions reduced by 14.47%, and the NO_x emissions reduced by 9.53%. However, the vehicle emissions reduction objective of the WPCPE was not reached.

Table 11. Comparison of energy consumption and emissions at different travel distances in the holidays.

Scenarios	Travel-Mode Chain								Energy Consumption Changes	CO_2 Changes	CO Changes	NO_x Changes
	1	3	4	5	34	35	45	345				
Benchmark scenario	1.52%	19.44%	29.55%	6.31%	34.34%	1.77%	2.78%	4.29%	0.00%	0.00%	0.00%	0.00%
Travel distance decreases by 5%	1.63%	20.30%	29.46%	5.84%	34.14%	1.77%	2.64%	4.22%	−3.57%	−2.59%	−5.41%	−3.66%
Travel distance decreases by 10%	1.75%	21.19%	29.33%	5.41%	33.89%	1.78%	2.50%	4.14%	−7.40%	−5.58%	−11.11%	−7.43%
Travel distance decreases by 15%	1.89%	22.13%	29.16%	5.01%	33.60%	1.78%	2.37%	4.06%	−9.71%	−7.59%	−14.47%	−9.53%

Table 12. Comparison of energy consumption and emissions under different car trip times in the holidays.

Scenarios	Travel-Mode Chain								Energy Consumption Changes	CO_2 Changes	CO Changes	NO_x Changes
	1	3	4	5	34	35	45	345				
Benchmark scenario	1.52%	19.44%	29.55%	6.31%	34.34%	1.77%	2.78%	4.29%	0.00%	0.00%	0.00%	0.00%
Car trip time increases by 5%	1.51%	19.51%	29.58%	6.08%	34.48%	1.77%	2.78%	4.30%	−1.78%	−1.15%	−2.75%	−1.94%
Car trip time increases by 10%	1.51%	19.57%	29.61%	5.86%	34.61%	1.76%	2.77%	4.31%	−3.56%	−2.40%	−5.47%	−3.81%
Car trip time increases by 20%	1.51%	19.69%	29.66%	5.44%	34.87%	1.75%	2.76%	4.32%	−5.33%	−3.56%	−8.22%	−5.75%

Table 13. Comparison of energy consumption and emissions under different holiday activity points.

Scenarios	Travel-Mode Chain								Energy Consumption Changes	CO_2 Changes	CO Changes	NO_x Changes
	1	3	4	5	34	35	45	345				
Benchmark scenario	1.52%	19.44%	29.55%	6.31%	34.34%	1.77%	2.78%	4.29%	0.00%	0.00%	0.00%	0.00%
One activity point	1.58%	22.38%	35.27%	5.63%	29.85%	0.87%	2.37%	2.05%	−10.37%	−7.49%	−14.65%	−11.25%
Two activity points	0.00%	16.91%	21.10%	8.16%	40.98%	2.86%	3.61%	6.39%	19.41%	13.55%	27.34%	21.56%
Three activity points	0.00%	9.88%	9.72%	9.81%	44.44%	6.87%	4.21%	15.08%	48.57%	33.82%	70.16%	53.21%

It was found that cars had the highest emission and energy consumption factors compared with the other trip modes. Reducing the trip mode split of cars saved a lot of energy consumption and reduced pollutants and carbon emissions. This study only increased the trip time of cars within a holiday tour, and compared the energy consumption and emissions under three policy scenarios with the benchmark scenario. The three scenarios were to lengthen the trip time of cars by 5, 10, and 20%, separately, and the results are shown in Table 12. The results showed that increasing the trip time of cars could reduce the proportion of car chains in the holidays to some extent. The reduced portion of the car chain was mainly attracted by public transport. When the trip time of a car was reduced by 20%, the energy consumption reduction could meet the levels of the WPCPE (2013–2017). However, although the vehicle emissions reduced with an increase of car trip time, they could not satisfy the target of a 25% reduction in every type of vehicle emission.

The two policies analyzed above were provided from the tour perspective and this study proposed another policy from an activity viewpoint. The method of predictive margins (also known as recycled predictions) was used, where the characteristics of interest were varied across the whole dataset. The difference in the calculated probabilities was the difference due to the number of activity points holding the other characteristics constant (results are shown in Table 13). There were three scenarios, which allocated the people in the dataset with one activity point, two activity points, and three activity points, respectively. It was found that the proportion of slow traffic, bus chains, and subway chains decreased significantly with an increase in activity points. The reduced portion was mainly attracted by the bus–subway–car chain, bus–subway chain, and bus–car chain. When the dataset only had one activity point in the holidays, energy consumption reduced by 10.37%, while the vehicle emissions of CO_2, CO, and NO_x reduced by 7.49, 14.65, and 11.25%, respectively. When the dataset had more than two activity points in the holidays, the energy consumption and vehicle emissions increased significantly.

6. Conclusions and Policy Implications

This study combined the activity-based travel demand model with the emissions model to investigate the relationship between people's activity travel scheduling and vehicle energy consumption and emissions during the holidays. Data were collected through a holiday travel behavior survey at Xidan and the Summer Palace during the 2012 Tomb-Sweeping Day holiday period. The survey applied a postal survey combined with a face-to-face interview, and 1688 questionnaires were distributed with 415 effective samples obtained. Based on the survey data, a multinomial logistic regression model was built to explore the decision mechanisms of individual travel-mode chain choices in the holidays that considered the influence of socio-demographic characteristics, travel characteristics, and activity characteristics. Second, the emissions estimation method was integrated with the activity-based travel demand model to calculate and compare vehicle energy consumption and emissions under different policy scenarios. The findings are summarized below:

For the effect of socio-demographic characteristics, the choice of holiday travel-mode chains was mainly influenced by personal income and physical strength. People aged above 50 years old seldom take car or combined mode as their travel-mode in holidays, and about one-third of bus–subway chains travellers are students without income. So, the car travellers are mainly from 20 to 50 years old with higher personal income. Therefore, policy makers should pay more attention to these part of travellers, and try to induce them to public transport and P&R travel-mode in holidays.

To obtain the effects of the activity characteristics, different activity locations had different transportation infrastructure and activity-travel patterns. Thus, corresponding policies could be made based on the travel characteristics of different regions. Moreover, the combined mode chains had more activity points than the single mode chains, and the proportion of slow traffic, bus chains, and subway chains decreased significantly with an increase in activity points. When everyone only had one activity point in the holidays, energy consumption reduced by 10.37%, while the vehicle emissions of CO_2, CO, and NO_x reduced by 7.49, 14.65, and 11.25%, respectively. Therefore, urban planners could focus on the construction of comprehensive leisure and entertainment places in Beijing, which would increase people's activity time and reduce the number of their activity points during the holidays.

For the effects of travel characteristics, car travelers had a higher sensitivity for walking distance than subway travelers. With the advantage of fast travel speed, the car chain had longer travel distances with shorter travel times. However, the probability for selecting the car chain dropped fastest when travel time increased in the holidays, and the reduced portion was mainly attracted by public transport. When the trip time by car reduced by 20%, energy consumption decreased by 5.33%, while the vehicle emissions were also reduced to some extent. Therefore, there are recommendations to decrease the travel proportion of cars, such as limitations on car speed, increasing bus speeds, and so on.

Moreover, the decrease of travel distance increased the proportion of slow traffic and bus chains in the holidays, which were mainly transferred from the car chain. Vehicle energy consumption and emissions were greatly reduced with adjustments to the activity-travel patterns in the holidays. This means that shortening holiday travel distance within Beijing is a good method to save energy consumption and reduce vehicle emissions. There are some additional recommendations including: (1) providing available travel information to the car travelers with shorter travel distance; (2) improving the attraction of the scenic spots or shopping malls near residential areas. This advice was linked with the construction of comprehensive leisure and entertainment places in Beijing, which would reduce the number of activity points and decrease their travel distance at the same time.

It should be noted that although a target of a 5% cut from vehicle energy consumption could be reached under most policy scenarios, the target of a 25% reduction in every kind of vehicle emission is very difficult to satisfy. That means that the goal of energy saving and emissions reduction cannot be achieved through a single policy strategy, and portfolio policies could have more significant effects. Therefore, a combined strategy for these three policies should be considered.

Given increasing concern for energy and environmental problems, it is important for urban planners and policy makers to understand the mechanisms influencing people's travel and activities in the holidays on vehicle energy consumption and emissions. The findings of this study could help develop more efficient policies to save energy and reduce carbon and pollutant emissions in the holiday period. It should be noted that the influencing relationship will change at different survey locations and different times, and the recommendations are not invariable with the change of external conditions. Therefore, the dynamic relationships of holiday activity–travel patterns with transportation energy consumption and emissions need further study. Additional work in this field is to again conduct the survey across different years with larger samples to explore the dynamic influencing mechanisms and provide general policies in the long-term.

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