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The impact of traffic demand management policy mix on commuter travel choices

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ABSTRACT

The experience of traffic demand management policy in many cities shows that a single policy instrument has limited effect and may have side effects on other contemporaneous policies; therefore, formulating a policy mix is a more effective way to solve urban traffic problems. However, the bulk of previous literature has focused on the impact of single policy instruments, neglecting the growing interest in understanding the role played by the different combinations of policy instruments. Therefore, using a 6*3 matrix typology, this paper provides an empirical impact analysis of selected policy mixes in inducing sustainable travel behavior and reducing private car use. This study also designs orthogonal experiments and adopts stated preference questionnaires to analyze the main effects and full combined effects of packages of policy instruments through multinomial logit models. The results show that the effect of a policy mix is often not better than that of a single policy and demonstrate the need for careful systemic design. A balanced-designed policy mix can facilitate public transportation and help reduce traffic gridlock using a balanced combination of push, pull and systemic TDM policy instruments.

1. Introduction

An urban traffic system is a huge dynamic system involving multiple modes of travel, thus even the same policy mix will have diversified impacts on different travel modes. An essential precondition for the effectiveness of policy instruments is whether the local population's behavioral response is consistent with expectations. Therefore, before the TDM policy is implemented, anticipating travel behavior choices becomes an important reference for the evaluation of policy impacts and will facilitate the design of the policy instrument (Cao and Mokhtarian, 2005; Rotaris and Danielis, 2014).

Various studies have been devoted to understanding the dynamics, characteristics and determinants of a sustainable traffic demand management system (TDM system) and the primary role played by public TDM policies (Feng et al., 2017; Xing et al., 2010; Ding et al., 2017). The bulk of previous literature has focused on the impact of single TDM policy instruments (Borjesson and Kristoffersson, 2018; Hounsell et al., 2011; Caicedo, 2012). However, traffic management requires the implementation of multiple policies to influence the whole range of agents involved (Sovacool, 2009). Furthermore, TDM policies are usually implemented in parallel with each other leading to ambiguous combination effects which call for further exploration.

Therefore, there is growing interest in understanding the role played by the different combinations of the available policy instruments, especially their interactions, in stimulating appropriate travelers' behavior and managing the traffic demand. Different combinations of instruments can have a variety of effects which may range from complementarity to counter-productivity (Habibian and Kermanshah, 2011; Habibian and Kermanshah 2013; May et al., 2006).

Recent empirical contributions demonstrate that TDM policy instruments mainly belong to two broad categories of "push" and "pull" instruments (Habibian and Kermanshah, 2011; Eriksson et al., 2010). However, the simple classification of push and pull policy instruments is too narrow and may lead to an insufficient understanding of the role of TDM policies (Kern and Howlett, 2009). Therefore, this study proposes a more balanced 6*3 matrix typology that combines six types (May et al., 2012) and three mechanisms (push, pull and systemic measures). Systemic measures in the typology are defined as involving both push and pull elements and influencing the transport system and its users as a whole, as suggested by Rogge and Reichardt (2016). An example would be educational policies which encourage users to change their travel habits.

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In the same vein, this study tries to provide an empirical investigation of the role played by different combinations of TDM policy instruments from the perspective of multiple travel mode choices in Beijing. The policy instruments will be classified with a matrix typology and regrouped to constitute possible policy mixes. Subsequently, the evaluations focus on the effects of policy mixes on travelers' behavioral choices using a stated preference experiment survey (Eboli and Mazzulla, 2008) with an orthogonal experimental design (Vaughan, 1993) schema. In doing so, we aim at deriving a policy mix analysis framework that assists in a more systemic understanding of real-world TDM policy mixes, serves as the basis for empirical analyses addressing the role of policy mixes for sustainable traffic demand management.

2. Literature review

The analysis of traffic demand management policies has constituted an empirical issue that has given rise to a flourishing literature (Loukopoulos et al., 2004). In particular, the literature has identified different types of TDM policy instruments that have been classified in two categories which mainly refer to "push" and "pull". More specifically, push measures discourage private car usage while pull measures encourage other alternative modes.

2.1. The typology of distinct policies

Extensive literature has been devoted to investigating the effectiveness of distinct TDM policies. For instance, Braun et al. (2016) evaluates the impact of TDM policy on commuters in Barcelona city center to abandon driving and choose to ride a bicycle. Adding public transportation sites and providing public traffic-oriented incentives can also affect the usability of bicycles (Braun et al., 2016). Zaman et al. (2011) observe that the choice of private car mode in Edmonton is not sensitive to travel time and cost.

Various studies have explored the effect of transport policies based on push/pull framework (May 2015). E.g., "*Effectiveness ratings of pull and push policy measures showed motorists would rather be pulled than pushed from their cars; that the old, the poor and urban dwellers would be more susceptible to push measures*" (Beatty, 2000). Eriksson et al. (2008) analyzed the combined effect of push and pull strategy, found that the pull measures were perceived to be effective and acceptable, the push measures and the combined packages were perceived to be rather ineffective and unacceptable. Therefore, a balance between both 'push' and 'pull' measures was striven for (Cools et al., 2012). Therefore, we classify the TDM policies by using an extended and further classified pull/push framework.

In summary, from the perspective of concrete approaches, we can follow the contribution of May (2012) to classify the TDM policies into six instrument types. From the perspective of interaction mechanism, as shown in Table 1, TDM policy instruments could be classified into three dimensions of pull, push and systemic, where systemic measures involving both push and pull elements and influencing the transport system and its users as a whole.

The push-pull-systemic typology is used here to provide a better understanding of the policy measures, and the core of the issue is not whether incentives or sticks are being used, but the causal chain expected from the policy mixes. Since the current understanding of the mechanism of complementarity and counterproductivity among policy measures is not clear, an empirical analysis will be adopted in this study to further verifying the mechanism through the push-pull-systemic framework. A wise combination of "push-pull" policy measures may have better performance than randomly selected combinations.

2.2. The role of policy mix

Naturally, all distinct policies have their limitations and barriers (May et al., 2006; Justen et al., 2014). Fortunately, through the combination of policy measures, the benefit of distinct policy instruments can be reinforced by others (May and Roberts, 1995), and implementing barriers can be removed (May et al., 2005). However, one of the main challenges of policy packaging is to evaluate the efficiency of the packages (Givoni and Moshe, 2014). However, the number of contributions that systemically examine the interaction between different policies in the context of traffic demand management is in fact limited, but gaining increasing interest.

Studies that focus on the effects of TDM policy mixes represent a limited though expanding area of research, as shown in Table 2. Combined with building more public transport infrastructure in Berlin, the information provision policies further increase the attractiveness of public transport (Miyamoto et al., 2004). Bueno 's (2017) study discovers that subsidies for private cars have a significant negative impact on the use of public transportation or cycling. Rotaris and Danielis (2014, 2015) conducted a case study at the University of Trieste, Italy, of different policy mixes on the university commuters. It is found that when fully subsidizing bus fares combined with introducing a parking

Table 1
Type-mechanism based instrument typology (with policy examples).

MAIN TYPE	PRIMARY MECHANISM		
	Push	Pull	Systemic
Land use	Restrict the amount of parking spaces (Santos et al., 2010)	P + R (Park and Ride); PT (public transportation) focused development; Pedestrian crossing facilities	Sustainable city masterplan; Development densities mix (May and Jiang, 2009)
Infrastructure	Control the construction of new roads in high density urban areas	Improvement of the bus/subway transfer (Valdes et al., 2016); Light rail systems; Cycling-friendly environment	Lane priority distribution system (Guzman et al., 2015)
Management & service	Restriction to enter bus lane during peak hours; Traffic restrictions based on the last digit of license plate numbers; Vehicle emission restriction; Traffic calming	Promotion of ride sharing; HOV lanes; Carpooling clubs Bike-sharing Forecast or reservations	UTC (Urban Traffic Control) system
Pricing	Congestion Charging (Deng and Feng, 2014); Fuel Surcharge (Wu et al., 2017); Road Pricing (Khoo et al., 2012); Parking fee	Discount of public transportation fare	Tax and subsidy reforms;
Attitudinal and behavioral policy	PSAs (Public Service Advertisements) about vehicle emissions	Publicity of green travel modes through public media (Santos et al., 2010);	Flexible working hours; Workplace travel plan
Information provision	Restriction signs and markings	Real-time bus arrival information; (Watkins et al., 2011; Wunderlich et al., 2017; Yun et al., 2017); Space availability information	Intelligent transportation system (ITS); Telecommunications

Source: Own elaboration (based on Habibian and Kermanshah, 2011, 2013; May et al., 2012; Miyamoto et al., 2004; Feng et al., 2017; Bueno et al., 2017; Borjesson and Kristoffersson, 2018).

Table 2
Studies estimating the effect of TDM policy packages on travel behavior.

	Methodology	Context	Policy Typology	Policy Instruments	Policy Interaction	Travel behavior
Habibian and Kermanshah (2013)	Stated preferences survey, MNL model	Tehran	Pull & Push	Increasing parking cost, Cordon pricing, Increasing fuel cost, Transit time reduction, Transit access improvement	3 policy pairs: Interaction of push measures, Interaction of pull measures	Mode choice: car, walk&ride, taxi, drive&ride, tel-taxi, motorcycle
Rotaris and Danielis (2014)	Stated preference experiments, ML and MNL model	Trieste, Italy	Policies which increase the cost of traveling by car and policies deals with the bus users' costs	Annual parking permit, Hourly parking tariff, Number of parking spaces, The location of parking facilities, one-way ticket, monthly ticket	2 policy pairs: Parking pricing and restrictions; Cutting both bus and parking subsidies	Mode choice: car, bus
Rotaris and Danielis (2015)					3 policy pairs: parking permit, hourly parking tariff and parking space; parking permit, hourly parking tariff and the location of parking areas; parking permit, hourly parking tariff and one-way ticket	
Braun et al. (2016)	Stated preference survey, conditional logit model	Barcelona, Spain	Pull	Increasing biking stations, incentives not to travel through private car, availability of public bus stations	Incentives for not to use private car to commute prove competition between public bus and bicycles	Mode choice: car, bus, bicycle, metro, tram
Feng et al. (2017)	Stackelberg game theory and travel choice based on Simulation	China	Pull &Push	Bus fare, additional private car toll, bus lane construction, and large-scale bus fleet purchase	Determine an optimal combination level of the 4 policy measures based on game theory and cost-benefit analysis	Mode choice: car, bus
Bueno et al. (2017)	Stated preference survey, MNL model	New York and New Jersay	Pull	Transportation benefits/subsidies, public transport accessibility	Workers with private car transportation benefits will reluctant to use public transport	Model choice: car, public transport, walk, bike
Nunes et al. (2019)	ASTRA-EC model, Simulation	Portugal	Market-based policies, Command-and-control and public investment policies	Congestion Fee; Gas Highway Tax; CO2 Tax; ICE Efficiency; Urban Logistics; EV Diffusion; Public Transportation	Full combinations	Mode choice: car, bus, train
Xu et al. (2019)	linear programming model, Simulation	Xiamen, China		BRT fare; taxi fare; bus fare; commuting-bus fare; oil price; dedicated bicycle routes	Full combinations	Commuting time estimation
Zhang et al. (2019)	City level data, HCW method	215 cities in China	car restriction policies	driving restriction policy and car license plate restriction policy	1 policy pair	Mode choice: usage of public transport
This paper	stated preference experiments, MNL model	Beijing, China	6*3 matrix typology	flexible working system, real-time bus arrival information, improvement of the bus/subway transfer, adding parking lots near subway stations, congestion charge, license plate restrictions, parking fees	Full combinations	Mode choice: Car, Taxi, Carpooling, Bicycle, Subway, Bus, P&R

tariff/fee, the mode split choice will be greatly affected. Feng et al. (2017) analyze the combination strength of TDM policy mix towards sustainable mode split. The result shows that the combined impact tends to be context-specific depending on the concrete environments and instrument features in specific countries.

The synergistic effect of TDM policy instruments has been further defined and illustrated by May et al. (2012). The authors introduced a decision support tool which generates possible policy combination packages based on KonSULT framework. The combination effect of more than two TDM policy instruments has been simulated using the MARS model (Pfaffenbichler et al., 2008). However, the result is based on the principle of systems dynamic simulations and the experience of European cities; whether it is suitable for other regions needs further exploration.

Other simulation researches also find that policy packages are effective at changing travelers' travel mode and reducing commuting time. Nunes et al. (2019) estimate the impacts of policy mixes including congestion fee and highway gas taxes. The results from Portuguese passengers show that these policies can effectively reduce passengers' car usage by 2.0%–5.4%. Xu et al. (2019) estimate the commuting cost under 63 combinations of six transport policies. They found that policy packages are effective in decreasing minimum commuting time (from 28.97 to 17.97 min).

Besides, the existing policy mix studies tend to be limited to examining instrument interactions. As shown in Table 2, current literature usually focused on 2 or 3 pairs of policy packages without considering the full combination effect of the entire policy package. However, in the real-world application, the coordination of different transportation departments is usually insufficient, and different policy instruments implemented by multiple departments often co-exist in the transportation system. Furthermore, an urban traffic system is a huge dynamic system involving multiple modes of travel, thus even the same policy mix will have diversified impacts on different travel modes. Therefore, the proposed paper enriches the current study by estimating the full combination effect of push, pull and systemic TDM policies on travel mode choice in complex transportation systems.

3. Research design

3.1. Policy selection and level determination

Based on the literature review and semi-structured interview, the most characteristic TDM policy instruments currently being implemented or discussed in Beijing have been selected as shown in Table 3. Each instrument in Table 3 represents the most promising and feasible policy in its own policy type, implying not only academic value but also attracting decision makers' attentions. For example, Beijing is planning to employ a congestion charge in pricing policies but still hesitated due to the uncertainty about its effect and public acceptability.

Three levels were selected for each of the seven policies based on

Table 3
Policy instrument level design.

Policy	Level 1	Level 2	Level 3
flexible working system(x1)	No flexibility (0)	postponed by 1 hour	Work at home
real-time bus arrival information(x2)	No	Error less than 10 mins	Error less than 1 min
improvement of the bus/subway transfer(x3)	No time is saved	Save 30% of time	Save 50% of time
adding parking lots near subway stations(x4)	20 mins in looking for parking space	10 mins in looking for parking space	5 mins in looking for parking space
congestion charge(x5)	0.5 Yuan per car per km	1 Yuan per car per km	2 Yuan per car per km
traffic restrictions based on the last digit of license plate numbers(x6)	No restriction	Restriction of two digits per day	Restriction of five digits per day
Parking fees(x7)	20 Yuan per car per hour	30 Yuan per car per hour	50 Yuan per car per hour

application experience in Beijing (see also A.2). After that, a stated preference questionnaire survey has been employed to investigate the travelers' responses to different TDM policy mixes. To be more specific, each policy mix with corresponding policy level will be considered as a scenario in the questionnaire, implying a full combination of 3ˆ7 = 2187 scenarios.

Setting the full combinations in the questionnaire would make the questionnaire too long and extremely cumbersome, thus influencing the experiment results. Instead, we use the orthogonal design approach (Street and Burgess, 2007) to design the questionnaire. Relying on the orthogonality of the table, optimized combinations can be selected for experiment while maintaining that each attribute level is evenly distributed among all choices. Therefore it can achieve the results equivalent to a large number of comprehensive tests with a minimum of test scenarios. Based on the policies and levels design in Table 3, this paper adopts the L18 (7,3) orthogonal table of 7 factors and 3 levels to

Suppose the local government will implement a transportation policy package. Which travel mode will you choose when facing the following policy scenarios? (Fill in the letter of your preferred travel mode in the bracket below each scenario)

A. Car B. Taxi C. Carpooling D. Bicycle E. Subway F. Bus G. Park and ride

	Scenario 1
Flexible working system	Work at home
Real-time bus arrival information	No
Improvement of the bus/subway transfer	No time is saved
Adding parking lots near subway stations	5 mins in looking for parking space
Congestion charge	0.5 Yuan per car per km
License plate number restriction	No restriction
Parking fees	20 Yuan per car per hour
Your travel mode choice	( )

Fig. 1. An example of SP questions.

evenly combine different traffic demand management policies and levels, therefore, 18 scenarios have been chosen to form the orthogonal experiment table (please refer to Annex A.1).

3.2. Survey design and data collection

The questionnaire used in this study is divided into three sections of socioeconomic characteristics, commuting features and habits, and stated preference experiments of different scenarios. More specifically, given the combination of policy instruments derived from orthogonal experimental design, commuters are asked to choose which of seven travel modes they would use under each scenario with a given combination. Please note that in this survey, we did not separate private bicycles from shared bicycles, so the bicycle mode here includes a combination of bicycle sharing, private bicycles, etc. Fig. 1 shows an example. To avoid too many trials that increase respondents' fatigue, in this part, each respondent is only required to answer 9 random questions. Combined with orthogonal design approach, the scenario questions for each respondent have been further decreased from 2187 to 9, therefore avoiding recognition bias (Ricchiute, 1997).

We took a number of steps to ensure complete responses and control the quality of data. First, to encourage respondents to answer the questions seriously, a cash reward of 5 yuan, or approximately $0.77 US, was attached to each questionnaire. Respondents could withdraw the reward directly after they finished the questionnaire. Second, to avoid respondents being exhausted before they fill in difficult questions, we placed the substantive investigation questions (i.e., the SP scenarios and mode choice questions) before those on the respondents' background information (Hensher et al., 2005). Third, prior to the formal launch of the questionnaire, two rounds of online and offline pilot studies were conducted using the above methods, each with between 30 and 50 respondents. Based on the results and feedback from the pilot studies, the number of policies and their attributes using for the scenario design were adjusted to control the difficulty of the questionnaire. We also amended the survey construction and the visual design to make the questions easier to answer for respondents. Fourth, three criteria were used to eliminate invalid answers: 1) large numbers of missing values; 2) extremely short response times; 3) straight-line responses. For respondents who have not finished all the questions, finished the questionnaire in less than 2 min, or have the same answer under all the scenarios, their questionnaires have been excluded to control for the quality of the data.

This study employs online questionnaires to solicit respondents and stated preference experiments are adopted to test their mode choice tendency under different TDM policy mixes. The web-based survey was deployed using the largest professional survey website in China (https://www.wjx.cn/). We distributed the link to our questionnaire via E-mail, WeChat and telephone. Since the policy instruments are selected based on the Beijing context, we only use Beijing regular commuters as our sample using screening questions. After the screening and validation process, a total of 600 questionnaires were collected, 429 of which were valid (71.5%), including a total of 3861 experimental observations. The descriptive statistics of the final sample are presented in Table 4.

Among the respondents, 61.07% were female (the percentage of female in Beijing in 2018 is 50.3%[1]) and 79.02% were under 40 years old (the percentage of residents from 0 to 39 years old in 2018 is 51.6%[1]). Hence, the samples have more female and younger respondents than the overall Beijing population, may be because young population constitute the major part of commuters; according to labor survey of statistic department, 70.2% of labor force in Beijing is below the age of 50, which is basically in line with our sample (CSY, 2017). However, it is clear that there are slightly more female in the sample. Besides, 76.92%

[1] http://tjj.beijing.gov.cn/tjsj/cysj/201905/t20190516_153984.html. Accessed Jan 16, 2020.

Table 4
Description of sampled commuters.

Socio-demographic attributes		No.	Pct. (%)
gender	female	262	61.07%
	male	167	38.93%
age	≤20	19	4.43%
	21–30	153	35.66%
	31–40	167	38.93%
	41–50	60	13.99%
	>50	30	6.99%
Education level	High school and below	35	8.16%
	Associate degree	64	14.92%
	Bachelor's degree	270	62.94%
	Master's degree	53	12.35%
	Doctoral degree	7	1.63%
Job type	student	48	11.19%
	worker	29	6.76%
	government officers	35	8.16%
	Business and service industry personnel	48	11.19%
	Business operation and management officer	98	22.84%
	Science/Education/Culture/ Health Management	41	9.56%
	self-employed or freelancers	11	2.56%
	Art & sport personnel	4	0.93%
	joint venture & sole proprietorship company staff	70	16.32%
	other	45	10.49%
Monthly income	Less than ¥4500	99	23.08%
	4500¥ ~ 8000¥	145	33.80%
	8000¥ ~ 15000¥	136	31.70%
	more than 15000¥	49	11.42%
marriage	Married and with kids	254	59.21%
	Married and no kids	38	8.86%
	Single and no kids	121	28.21%
	Single and have kid(s)	8	1.86%
Number of family members	1	81	18.88%
	2	110	25.64%
	3	170	39.63%
	4 and above	68	15.85%
Car ownership	0	119	27.74%
	1	274	63.87%
	2	30	6.99%
	3 and above	6	1.40%
Ring Road number of residences	inside the 2nd ring road	25	5.83%
	2nd to 3rd ring road	69	16.08%
	3rd to 4th ring road	86	20.05%
	4th to 5th ring road	102	23.78%
	5th to 6th ring road	102	23.78%
	outside the 6th ring road	45	10.49%
Ring Road number of workplaces	inside the 2nd ring road	44	10.26%
	2nd to 3rd ring road	100	23.31%
	3rd to 4th ring road	113	26.34%
	4th to 5th ring road	83	19.35%
	5th to 6th ring road	56	13.05%
	outside the 6th ring road	33	7.69%
commuting distance	Up to 5 km	83	19.35%
	5 km–10 km	91	21.21%
	10 km–15 km	106	24.71%
	15 km–20 km	72	16.78%
	More than 20 km	77	17.95%
Usual commute mode	driving	94	21.91%
	taxi	6	1.40%
	sharing	18	4.20%
	bicycle	45	10.49%
	subway	149	34.73%
	bus	85	19.81%
	drivesub	19	4.43%
the days of weekly driving	0	155	36.13%
	1–2	99	23.08%
	3–4	68	15.85%
	5	79	18.41%
	More than 5 days	28	6.53%
Normal departure time	6am ~ 7am	121	28.21%
	7am ~ 8am	199	46.39%
	8am ~ 9am	86	20.05%

(continued on next page)

Table 4 (*continued*)

Socio-demographic attributes		No.	Pct. (%)
	9am ~ 10am	12	2.80%
	Later than 10am	11	2.56%
Commuting time	30 min and below	101	23.54%
	30–60 min	243	56.64%
	60–90 min	63	14.69%
	90 min and above	22	5.13%
Work flexibility	0	124	28.90%
	1	184	42.89%
	2	93	21.68%
	3	21	4.90%
	4	7	1.63%
the days of work at home	0	281	65.50%
	1	44	10.26%
	2	63	14.69%
	3	19	4.43%
	4	9	2.10%
	5 and above	13	3.03%
Whether need to pick-up/ drop-off children	no need	328	76.46%
	need	101	23.54%

respondents were highly educated (bachelor's degree and above), which is due to the fact that the education threshold in Beijing is high to find a job. Moreover, 65.5% of the respondents had monthly income between ¥4500 and ¥15000 (the 2018 mean per capita monthly income for Beijing is about ¥7855[1]). Besides, their occupations are dispersed and about 90% of them live and work inside the sixth ring road, which are representative of typical Beijing commuters (2019 Beijing traffic development annual report). According to the commuting attributes, more than 70% of our sample have at least one car. 66.44% respondents normally commute between 7.00 am and 9.00 am, which is the morning peak hour in Beijing. About 24.71% of our commuters' commuting distance is from 10 km to 15 km and the commuting time of the majority is from 30 to 60 min, which is the average commuting distance and commuting time of Beijing commuters (2019 Beijing traffic development annual report). Besides, the majority of our sample have less temporal and spatial working flexibility.

3.3. Model building

This study employs the Mixed Logit Model to estimate the coefficients. The dependent variable is set as the choice of travel mode for commuters under the influence of selected independent factors and various policy mix scenarios. The options include 7 alternatives as shown in Fig. 2. As shown in Table 5, the independent variables include the selected 7 distinct policies and their corresponding policy mixes; the 18 social demographic factors and 17 commuting characteristics.

Since all the other considering variables are only individual-specific which does not change according to different mode choices, only alternative-specific constants were mixed to account for the panel effect (Train, 2009; Thorhauge et al., 2016; Ning et al., 2017). The utility function of our model is shown below:

$$U_{jnt} = ASC_j + \beta_j^p p_t + \beta_j x_n + \mu_{jn} + \varepsilon_{jnt} \tag{1}$$

where U_{jnt} is the utility for individual n associated with alternative j in scenario t. ASC_j is the alternative specific constant for alterative j. β_j^p and β_j are two vectors of coefficients of policy variables p_t and other individual specific variables x_n separately. μ_{jn} follows a normal distribution across individuals but it is constant across all the scenarios answered by the same respondent, which accounts for the panel correlation, while ε_{jnt} is a random term with *iid* extreme value distribution.

Table 5
Variable descriptions.

Aspect	Variable Description	Symbol
Policy	No flexible working time (Base case)	x1
	Can postpone 1 h to work	x1p1
	Work at home is available	x1wh
	real-time bus arrival information	x2
	improvement of the bus/subway transfer	x3
	adding parking lots near subway stations	x4
	congestion charge	x5
	traffic restrictions based on the last digit of license plate numbers	x6
	parking fees	x7
Social Demographic features	Gender	male
	Age	age
	Education level	edu
	worker	worker
	government officers	officer
	Business and service industry personnel	service
	Business operation and management officer	company
	Science/Education/Culture/Health Management	science
	self-employed or freelancers	individual
	Art & sport personnel	art
	joint venture & sole proprietorship company staff	joint
	income	income
	Married and have kids	mwk
	Married and no kids	mnk
	Single and no kids	notm
	Single and have kid(s)	swk
	Number of family members	member
	Car ownership	caro
Commute features	Ring Road number of residences	location1
	Ring Road number of workplaces	location2
	commuting distance	distance
	Usual commute mode is taxi	taxi
	Usual commute mode is car/carpooling	car
	Usual commute mode is bicycle	bicycle
	Usual commute mode is subway	subway
	Usual commute mode is bus	bus
	Usual commute mode is park and ride	drivesub
	the days of weekly driving	drivingday
	Departure time	leavingtime
	Commuting time	duration
	Work flexibility	flexible
	the days of work at home	homeworking
	Whether need to pick-up/drop-off children	pick

4. Result analysis

4.1. Mixed logit estimation on distinct TDM policies

The first part of the empirical analysis follows the contributions discussed in section III.3 and refers to the estimation of a baseline model, in which the role played by each single TDM policy in shaping travel model choices is tested.

As reported in Table 6, the endogeneity and multicollinearity are well-controlled with no evidence against H0 assumption in Hausman test and the average VIF value equals 1.61.

The estimation results also use the form of marginal effects, therefore better represent the marginal effects of distinct policy instruments. Since the mixed logit model is a non-linear regression model, the marginal effects of the corresponding explanatory variables are not constants, but vary with different values of the independent variables. Hence, for each independent variable, the marginal effects are different at each level of that variable. Equations (2)–(4) show an example of a binary logit model. The deviation of p_i with respect to x (Eq. (4)) is the marginal effect when x is a continuous variable. When x is a categorical variable (e.g., dummy variable), we can predict p_i for $x = 1$ and $x = 0$ separately, and compute the difference between these two probabilities. Here we

Table 6
Panel effect mixed logit model estimation criteria on TDM policies.

	Criteria	Results
Alternative specific constant	Taxi	−0.982
	Carpooling	−2.420
	Bicycle	−3.990
	Subway	−0.884
	Bus	−0.713
	Parkride	−2.720
Standard deviations	ASC_Taxi	1.510***
	ASC_Carpooling	0.563***
	ASC_Bicycle	1.970***
	ASC_Subway	1.270***
	ASC_Bus	1.450***
	ASC_Parkride	2.420***
	ASC_Car	2.370***
Number of observations	3861	
Average VIF	1.61	
Hausman Test ($P > chi^2$)	No evidence against H_0	
Rho-square	0.182	
Log likelihood	−4931.651	
AIC	10319.3	
BIC	11245.31	

can see, no matter what kind of x, the marginal effect of a logit model is not a constant but depends on the value of x.

$$\ln\left(\frac{p_i}{1-p_i}\right)=\beta_0+\beta_1 x \tag{2}$$

$$p_i=\frac{1}{e^{-(\beta_0+\beta_1 x)}} \tag{3}$$

$$\frac{dp_i}{dx}=-\frac{1}{\left[1+e^{-(\beta_0+\beta_1 x)}\right]^2}\cdot e^{-(\beta_0+\beta_1 x)}\cdot(-\beta_1) \tag{4}$$

In this study, the marginal effects (ME) for each participant and scenario are calculated using the observed values of each policy variable, while the values of all other independent variables remain unchanged. Then, we compute the average of all MEs to obtain the average marginal effect (AME). Therefore, this study adopts the average marginal effect (AME), which is to calculate the average value of the marginal effects of each participant and scenario at the observed value (Wuff, 2015).

Moreover, in the Beijing context, buses and subways do have differences, since the speed and waiting time for the bus strongly depends on road congestion situation, while Beijing has a serious congestion problem. In contrast, subways have almost fixed speeds, schedules and waiting times, which are more reliable than buses. Therefore, the buses and subways are usually perceived as different modes by users, with very different mode-specific constants. Our Hausman test also shows that there is no evidence against IIA assumption when separating bus and subway in the current estimation model (as shown in Table 6). Furthermore, the mixed logit model has been used in this study. It is more flexible than the standard logit model, and can relax the independence from irrelevant alternatives (IIA) assumption of the standard logit model because the ratio of mixed logit probabilities depends on all the data, including attributes of alternatives (Train, 2009). Studies that use the mixed logit model to estimate mode choice behavior also measure bus and subway as two independent modes (e.g., Shen, 2009; Agarwal et al., 2020; Deka and Carnegie, 2021).

4.1.1. Social demographics factors

From the estimation result of social demographic factors in Table 7, we can see that males are more inclined to ride bicycles. This may be related to the boom of bike sharing in China in recent years (Guo. et al., 2017). Bike-sharing is widely distributed in cities, and its ease of use has attracted a large number of sports enthusiasts, especially energetic males. In addition, the older the people are, the less likely are they to take travel modes requiring multiple transfers (P + R mode in the model). Considering physical condition of the senior population, this is an understandable tendency. Senior citizens also don't prefer taxis, they are in general more inclined to use the base case—the private cars as shown in Table 7. Those with higher education are more inclined to take taxis/carpools/bicycles/subways instead of private cars, this is also natural as the level of education is highly related to green travel awareness (Ho et al., 2017).

Marital status and whether or not the family have kids also influence commuters' mode choices. Those who are married with kids are more likely to choose P&R. On the other hand, people who are single but have kids are more inclined to use taxi. These results are logical given concern over safety for children and ease of combining travel to work and education.

The result suggests that people in science positions are more likely to travel by taxi or carpooling than public transport modes. Since they have higher income and consider more about comfort, they are not inclined to low-cost but time-consuming bicycles and buses. On the other hand, workers who have less stable income are more inclined to public transports and bicycles. Officers and service employees prefer carpooling, subway, bikes and subways.

4.1.2. Commute feature factors

In terms of commute features, as shown in Table 8, factors that have a significant impact on the choice of travel mode include workplace, common commute modes, days people drive to work (if they choose

Table 7
Estimation of social demographic factors.

Features	Taxi	Carpooling	Bicycle	Subway	Bus	Park and Ride
Male	−0.145	−0.217	0.022*	−0.345	−0.006	−0.350
Age	−0.556**	−0.334	0.061	−0.026	0.056	−0.278*
Education	0.625**	0.727***	0.694**	0.676***	0.332	0.442
Worker	1.320	1.310	2.440***	1.440**	1.580**	0.020
Officer	1.170	1.700**	1.350*	1.370**	1.480**	1.130
Service	1.050	1.900***	1.990**	1.760***	0.881	0.740
Manager	0.608	0.716	0.646	0.607	−0.208	−0.814
Science	1.980**	1.750**	1.470	1.150	1.080	0.307
Freelancer	0.766	1.240	0.672	−0.416	−0.545	−1.170
Art	−1.540	−1.320	0.743	−1.540	−1.120	−1.040
Joint	1.070	1.770***	−0.071	1.380**	1.010*	0.768
Income level	0.270	0.053	−0.105	0.040	−0.137	−0.159
Married with kids	0.228	0.265	−0.151	−0.226	0.063	0.975
Married no kids	−0.482	−1.380**	−1.540**	−0.788	−0.302	0.153
Single with kids	0.201	−10.500	−0.856	−2.770**	−0.274	−9.680
Family members	−0.830***	−0.683***	−0.633***	−0.232	−0.198	−0.400*
Car ownership	−0.576*	−0.368	−1.050***	−0.720***	−0.621**	−0.985**

Note:*** represents significance at 99% confidence level; ** represents significance at 95% confidence level; * represents significance at 90% confidence level.

Table 8
Estimation of commute feature factors.

Features	Taxi	Carpooling	Bicycle	Subway	Bus	Park and Ride
Work place	0.150	0.338***	0.227	0.185*	0.264**	0.121
Normal: car	−2.370***	−2.770***	−2.440***	−1.530***	−1.790***	−0.658
Normal: bicycle	1.120	0.448	3.390***	1.250**	1.610**	1.030
Normal: subway	−1.310**	−0.361	0.494	2.240***	1.410***	2.150***
Normal: bus	−0.708	−0.689	−0.036	0.888	2.270***	1.870**
Normal: P + R	−0.659	−0.566	−0.102	1.370*	1.580**	2.960***
Driving days	−0.193	0.017	0.070	−0.199	−0.244*	0.083
Departure time	0.122	−0.016	0.023	0.131	0.085	−0.164
Duration	0.454*	0.608**	0.589**	0.237	0.250	0.187
Flexible	0.432**	0.155	0.603***	0.185	0.177	0.169
Pick up children	1.280***	0.690*	0.815*	0.270	0.255	1.000**

Note: *** represents significance at 99% confidence level; ** represents significance at 95% confidence level; * represents significance at 90% confidence level.

driving as common travel mode), leaving time, working time flexibility, and whether they need to pick up/drop off children during the commute. The variable "work place" basically reflects the distance from the work place to the city center, so the further this distance is, the more likely it is that commuters will choose a taxi or subway, which is convenient and does not require driving by themselves or can guarantee punctuality.

For the common travel modes, it can be seen that people who have their own fixed travel modes are almost unwilling to change their travel behavior and choose other ways. For the variable of days people drive to work per week (driving days), results suggested that it is more difficult for the commuters who are used to driving to work to change their way of travel.

For those who already have a flexible work schedule, more significant results can be obtained compared with policy ×1 (flexible time schedule which will be discussed in section 4.1.3). The more flexible the working hour is, the more likely people are to choose taxi and bicycles. The possible reason is that the flexibility of working hours allows them to arrange travel more flexibly, therefore they find the low efficiency of bicycle becomes acceptable.

Meanwhile, commuters who need to pick up and drop off their children usually prefer to use taxi, carpooling and Park and Ride. This is also an intuitive result as parents tend to provide their children with a more comfortable and convenient travel environment. Bicycle is also preferred, possible explanation is that it is always difficult to find suitable temporary parking spots around the campus during peak hours because it is too crowded.

4.1.3. *The role played by single TDM policy instruments*

Regarding the role played by single policy instruments, the structure of orthogonal experiment design allows us to isolate the marginal effect and estimate the coefficients of single TDM policies. Due to the non-linear feature of the estimation model in this paper, the individual behavior at the sample mean differs from the average behavior of the individual samples. For policy analysis, it is usually more meaningful to use the average marginal effect of all sample points (Wuff, 2015). Therefore, the following part will evaluate the policy effects through the Average Marginal Effect (AME) analysis of mixed logit model.

Results reported in Table 9 show that push policy instruments such as congestion charge, restriction based on vehicle license number and parking fee will significantly increase the intentions to commute by public transport modes, bicycles, taxi and carpooling. While pull strategies also increase the adoption of public transport modes, e.g. improving the public transport transfer will significantly increase the usage of P&R mode (park and ride, commuting mode combining private and public transportation); improved real time bus information will increase the usage of public bus.

On the other hand, the systemic policy instrument:1 h postponed flexible work schedule (x1p1) discourages commuters in Beijing from using subway to work. Taxi or bicycle represents an acceptable alternative solution to flexible workers. Considering the serious traffic congestion and high population density in Beijing, driving experience is undesirable (Shen et al., 2018), crowded public transport environment is uncomfortable as well (Zhang et al., 2014). If commuters have flexible time schedule for work, they will prefer to travel by bicycle, taxi, or

Table 9
Estimation of single policy effects (AME marginal effects).

Policy	Taxi	Carpooling	Bicycle	Subway	Bus	Park and Ride
Flexible work (x1p1)	0.0030	0.0217	0.0363	-0.0965***	0.0213	0.0002
Flexible work (x1wh)	0.0091**	0.0007	0.0360**	0.0669	0.0245	-0.0056
Bus Infor. (x2)	0.0001	-0.0162	-0.0052	-0.0676	0.0876**	-0.0013
Improve transfer (x3)	-0.0302	-0.0433	-0.0114	0.0931	-0.0352	0.0372***
Improve parking near subway (x4)	0.0002	-0.0075	0.0014	0.0058	0.0011	0.0022**
Congestion fee (x5)	-0.0023	0.0101**	0.0076**	0.0153**	-0.0194	-0.0019
Restriction based on license number (x6)	-0.0009	0.0018	0.0061***	0.0049	0.0088	0.0001
Parking fee (x7)	0.0004**	0.0005**	0.0005**	0.0000	-0.0006	-0.0001

carpooling (although not significant) to enjoy their private space or don't have to drive by themselves.

From the perspective of the magnitude of the marginal effect, the most effective policy instrument is the pull strategy represented here by improving the public transport transfer, with the highest effects on the marginal effect of Park and Ride. However, when considering the impact on a range of modes, the push policy strategy, represented by parking fee/congestion charging fee also plays an important role to promote sustainable travel mode choices.

As shown in Table 9, restriction based on license number (x6) policy measure, although not all significant, generally promote more sustainable travel modes comparing with other policy measures.

The results discussed so far allow us to conclude that the role of TDM policies in driving public transportation or green travel behavior does, as expected, vary between policies.

4.2. The combinations of policy instruments

Moving to the analysis of results related to different policy mixes, as shown by results in Table 10, the adopted indicators measuring coefficients of corresponding policy mixes significantly enter the econometric model. All possible combinations of these 7 policy instruments have been tested using interaction terms, including all policy mixes with 2 policy instruments, 3 instruments, likewise. Therefore, in total 119 policy mixes have been tested and for simplicity we omitted all the insignificant policy mixes; the remaining significant policy mixes are as shown in Table 10.

The inclusion of policy interaction terms in the regressors may present econometric problems related to potential bias in estimations due to multicollinearity. In order to make the coefficients of the regression equation more explanatory, we mean-centered each scale that constitutes an interaction term and created the interaction terms by multiplying the relevant mean-centered scales (Bolin, 2014). The main effects (significance and marginal effect of non-interactive terms) did not change much after adopting the centered scale with interaction terms, therefore, this potential bias has been controlled in the model.

The most important finding is the countervailing effect. Although single TDM policy instruments play an important role in individual mode choice as shown in section 4.1.3, their combinations do not necessarily enhance each other's influence, and are sometimes even counterproductive. The marginal effects of many policy instruments are actually reduced when combined with other policy instruments, e.g.,

Table 10
Marginal effect of policy mixes (AME marginal effect).

Policy mix	Taxi	Car pooling	Bicycle	Subway	Bus	Park and Ride
x3x6	-0.0196	-0.0016	-0.0030	0.0257***	0.0132**	0.0006
x4x7	0.0042	0.0035	0.0195	-0.0257***	-0.0075*	-0.0053**
x1p1x7	0.0139*	0.0152*	0.0010	-0.0028	-0.0224	-0.0050
x1whx7	0.0112	-0.0092	0.0129	-0.0257	0.0081	0.0076
x2x6	-0.0105	-0.0030	-0.0136	0.0073*	0.0308***	0.0024
x2x4x7	0.0071	-0.0071**	-0.0044**	-0.0213***	0.0102*	0.0058
x3x4x6	-0.0085	-0.0053	-0.0126	0.0173***	0.0173***	0.0024*
x3x5x7	-0.0033	0.0026	0.0168***	0.0047	-0.0210	0.0039
x2x3x6	0.0036	0.0009	-0.0030	0.0234***	-0.0272	0.0081***
x2x3x4x7	0.0002	-0.0045**	-0.0052	0.0226	-0.0183	0.0052
x3x4x5x6	-0.0078	-0.0042	0.0078**	0.0186***	-0.0115	0.0058**
x1p1x2x3x6	0.0076**	0.0010*	0.0151***	0.0483***	-0.0502	-0.0013
x1whx2x3x6	-0.0053	0.0008	-0.0090	0.0342*	-0.0353	0.0198***
x2x3x5x6x7	0.0017	-0.0056**	-0.0069**	-0.0168***	0.0077	0.0091
x1p1x2x3x6x7	-0.0070*	-0.0270***	-0.0114*	-0.0093	0.0293	0.0140
x1whx2x3x6x7	0.0066	0.0048	0.0005	-0.0309**	0.0216	-0.0150***
x1p1x2x3x4x6x7	-0.0192	0.0211	-0.0190	0.0419	0.0353	-0.0300
x1whx2x3x4x6x7	0.0007	-0.0010	-0.0151**	0.0262	-0.0237	0.0137***
x1p1x2x3x5x6x7	-0.0098**	-0.0102**	-0.0033**	-0.0282***	0.0268	0.0084
x1whx2x3x5x6x7	0.0322	-0.00644	-0.0323***	-0.0136*	-0.0122*	0.0151
x2x3x4x5x6x7	0.0174	-0.0018**	-0.0011**	-0.0232***	-0.0114***	0.0023
x1p1x2x3x4x5x6x7	-0.0138	-0.00418	-0.0276	0.0689***	0.0169*	-0.0079
x1whx2x3x4x5x6x7	0.0297	-0.0032**	-0.0193***	-0.0373***	0.0082*	-0.0020**

when implemented separately, the pull policy that improves public transfer (x3) has a significant positive impact on the tendency of choosing P + R (driving + subway) mode. However, when it combines with a push strategy which restrict private cars based on license plate number (x6), the combined marginal effect to improve P + R has fallen to 0.0006 (when applied alone it was 0.0372) in Table 10. Possible explanation is that since the push policy has restricted the usage of private cars, even though the pull policy is improving the connections between driving and subway, the attractiveness of P&R (driving + subway) mode is still reduced. Consequently, commuters will tend to use alternative transportation modes. Therefore, in the context of urban comprehensive transportation system, individual response to TDM policies, especially multiple coexisting policies, becomes increasingly diverse and intricate.

Further analysis suggests that nothing guarantees that any combination of instruments is superior to a single TDM policy instrument approach. For policy mixes with two TDM policy instruments, combining policy instruments will lead to differentiated, context-specific policy performance.

The causal chain between policy instruments is important. For example, push strategy of restriction based on license number (x6) will increase the adoption of bicycle, subway and bus (as shown in Table 9); if it is combined with pull strategy of improve transfer (x3), their policy mix (x3x6) will significantly increase the tendency to choose subway and carpooling instead; and if combined with another pull strategy of real time bus info. (x2x6), commuters will be inclined to use subway and bus (Table 10).

Except for the policy mix of x2x6, no other policy mixes with only push or pull strategies are significant. The result implies that the balanced policy mix (push + pull) will better encourage the targeted mode of pull strategy (provide real-time bus information, a pull instrument designed for bus, therefore the policy mix precisely increases the tendency to choose bus), while the double push policy mix has forced taxi users switch to multiple alternative modes such as subway or carpooling, with scattered marginal effects. For systemic approach, the effect can be positive if combined with proper push policy (E.g. **x1p1**x7).

For policy mixes with more than two TDM policy instruments, multiple agents will be influenced, yielding complex and compromised impacts on various transport modes. For example, when implemented alone, the pull instrument of providing real time bus information (x2) can significantly increase individual tendency to choose bus, however, when it is combined with another pull instrument for P + R (x4, adding parking lots near subway), the marginal effect to encourage bus is largely compromised, therefore, it is not significant as a two-instruments policy mix (x2x4 is not significant, therefore omitted from Table 10). Yet the policy mix of x2x4 can still be significant if we add another push strategy (x7, parking fee) to shift more car users to alternative modes. Therefore, the policy mix of x2x4x7 can significantly increase the bus usage, however, with a reduced marginal effect of 0.0102.

The combined impact of x2x4x7 is significant but compromised due to the incompatible modal targets. Specifically, ×4 is designed for Park and Ride, however it will also increase the tendency to use private cars, while ×2 only intends to encourage the usage of public bus. The inconsistency of these two types of pull policies yields an offset impact, resulting in a poor overall effect of the policy mix. For P + R mode the marginal effect of the policy mix is negative while for public bus, the marginal effect is worse than the single policy of x2.

Important "policy partners" can also be identified using the proposed model. Note that although the pull policy of ×4 (adding parking lots near subway) has a significant positive effect to foster sustainable travel mode choice as discussed in section 4.1.3, when combined with the pull instrument of ×3 (improving public transfer), their corresponding policy mixes (x3x4x6, x2x3x4x7, x3x4x5x6, x1whx2x3x4x6x7) will also provide significant positive impulse to encourage Park and Ride mode. Therefore, the pull policy of ×4 needs to be implemented with partner policy instruments to play a positive role in encouraging P&R; this finding is consistent with the contribution of Duncan (Duncan and Cook, 2014). However, in attempting to further enhance the policy mix for x3x4, we can also find that complex combinations played a counter-productive effect. E.g., x1whx2x3x4x5x6x7 in Table 10, which is the complete set of all policy instruments in this paper, with the most flexible work schedule (x1wh), only significantly promotes the public bus mode with small marginal effect (0.0082), and positively promotes the travel by taxi and private cars.

Therefore, since not all the policy instruments are complementary to each other, it is also worth noting that an over complicated policy mix will lead to confused influences. For policy mixes with 4 or more policy instruments, the marginal effects are generally scattered and reduced, some even showing significant negative net effects, for example, x2x3x4x7 will significantly decrease the tendency of car-pooling when compared with private cars. Therefore, government departments should make a rigorous demonstration of the anticipated effects, and clarify the causal chain of policy impacts before implementing the new policy instruments, especially considering the combined effects of the new and existing policy instruments. Possible offsetting effects between policy instruments may lead to reduced effect or even unexpected counter-effects.

5. Discussion and policy implications

5.1. Single TDM policy instruments

All variables are transformed by taking natural logarithms data format and the average marginal effect has been estimated in Table 11 to represent the marginal effect of single policy instruments by percentage. The results show that a single policy instrument can play a major role in the choice of travel mode, but it does not necessarily reduces private car usage. For policy instruments of improve parking near subway and flexible work schedule, the private car usage actually increased, due to the reduced usage of other modes.

> Traffic restriction based on the last digit of license plate numbers is effective in driving people towards green travel. Moreover, the mandatory policy parking fee is the most effective to make people less willing to drive private car and turn to alternative modes such as taxi.

Real-time display of bus arrival information in the bus stop is an efficient way to improve bicycle and bus usage, meanwhile it will also marginally increase car usage and reduce all other types of travel modes. Improved transfer is also an important and efficient approach, it will increase subway and P&R usage. Flexible work schedule is complex, it

Table 11
Single policy effect (%) and typical alternatives.

Policy Instrument	Change in Private Car Usage (%)	Typical Increased Travel Modes	Typical Reduced Travel Modes
Flexible work (x1p1)	2.13%	All other modes	Subway, Bus
Flexible work (x1wh)	2.08%	Taxi, Carpooling, Bicycle	Subway, Bus, Park and Ride
Bus Infor. (x2)	0.06%	Bicycle, Bus	All other modes
Improve transfer (x3)	−0.30%	Subway, P&R	All other modes
Improve parking near subway (x4)	−0.81%	All other modes	Taxi, Carpooling
Congestion fee (x5)	−0.86%	Carpooling, Bicycle, Subway	Taxi, Bus, P&R
Restriction based on license number (x6)	−0.93%	Carpooling, Bicycle, Subway	Taxi, Bus, P&R
Parking fee (x7)	−2.27%	All other modes	Bus, P&R

will increase usage of bicycle, taxi and private car, but reduce the usage of subway, bus and P + R, since arrival on time is no longer the first priority, more comfortable (taxi, private car) or slower (but green) travel modes become their first alternatives.

It is interesting to notice that congestion fee also has a marginal effect on reducing bus travel. People originally choosing Park and Ride, taxi and bus will choose subway and bicycles instead. Considering taxi drivers and bus company can let passengers bear part of the congestion fee cost, this tendency is understandable. This also explains why the policy mixes sometimes have reduced net effect, since different policy instruments have different effects on the different travel modes.

5.2. Implication from policy mixes

As demonstrated in Table 12 (all policy mixes unable to significantly reduce private car usage have been omitted in this table), using more coexisting policy instruments does not necessarily guarantee larger overall positive effects. Possible offsetting effects between policy instruments may lead to reduced effect (reduced car usage is decreasing as policy number increases in Table 12) or even unexpected counter-effects. Therefore, governments need to ensure that national, regional and local transport strategies are based on a clearly agreed set of policy objectives. Multiple objectives may also lead to reduced net effects. For example, as discussed in section 4.2 about the policy mix x2x4x7, this finding is in line with the (May et al., 2012).

On the other hand, if carefully designed, the policy instruments can be complementary to each other (Harbibian and Kermanshah, 2011), for example, pull policy instruments may make commuters abandon private cars, and effective improvements of pull policy in public transport infrastructure can enable commuters to actively choose to travel by public transport. Therefore, a well-balanced combination of push and pull policy mixes can have good results (x2x6, x4x7, etc.). Besides, some policy instruments can only be positively effective if combined with their "partners", for example, the "policy partners" discussed in section 4.2. For example, the pull policy of ×2 (Bus Info.) applied alone can only reduce private car usage with 0.2% while combined with push policy of ×6 (Restriction based on license number), their policy mix can reduce the private car usage with 0.6%. This is a well-balanced example of complementary policy mixes.

The policy instruments have been classified into three groups of pull, push and systemic approaches. The results imply that the well-balanced policy mixes among pull, push and systemic can have potential effective performance, while multiple pull policy instruments with diversified objectives will lead to confused result. Therefore, governments should carefully design the solutions before implementation, especially the interaction between the new policy instrument and existing policy mixes.

The outlined empirical findings represent a step forward with regard to existing studies since they provide new insight for the design of a policy mix that aims to promote green or public travel modes. Moreover, the proposed methodology could be applied to other technological domains involving policy interactions.

Table 12
Policy mix effect (%) and typical alternatives.

Policy Instrument	Reduced Private Car Usage (%)	Typical Alternatives	Other Reduced Travel Modes
x1p1x7	0.58%	All other modes	Subway, Bus
x1whx7	0.60%	Taxi, Bicycle	All other modes
x4x7	−1.59%	All other modes	Carpooling
x2x6	−0.32%	Bicycle, Bus	All other modes
x2x3x6	−0.23%	Bus, P&R	All other modes
x1p1x2x3x6x7	−0.37%	Subway, Bus	All other modes
x1whx2x3x6x7	−0.43%	Carpooling, Bicycle, Subway	Taxi, Bus, Park and Ride
x1p1x2x3x5x6x7	−0.41%	Subway, Bus	All other modes
x1whx2x3x5x6x7	−0.56%	All other modes	Taxi
x1p1x2x3x4x5x6x7	−0.56%	Subway, Bus	All other modes

In conclusion, ignoring complementary or counterproductive interactions among policy instruments will lead to unexpected overall policy effects. Therefore, improved decision-support tools are needed to enable cities to anticipate and systemically analyze the combined effect of policy instruments.

5.3. Limitations

Considering the difficulties in examining the issue at stake, the data has been chosen considering the availability of statistical information suitable for a quantitative behavioral analysis. The data is only gathered from a stated preference experiment instead of a revealed preference experiment, therefore bias exists between the respondents' action and stated preference. Since perception of commuters may vary depending on different real-life scenarios, their behavior could be more complicated. Besides, there are more female commuters in the sample, so a certain sample bias cannot be avoided. Therefore, adopting the analysis framework in field experiment scenarios will be our next approach to avoid this bias in stated preference context.

Second, due to the exponential increasing possible combinations of policy instruments, we only choose 7 policy instruments with 3 different implementation levels, and the number of possible combinations already reaches 2187 scenarios. With the help of orthogonal experimental design, we reduced this number to 18. Therefore, the total number of policy instruments studied here is limited and only considered in the Beijing context. A more thorough analysis considering a larger scope of policy instruments in different areas could be fruitfully addressed by future research.

Another limitation is that this study only explores the commuting scenarios; other travel scenarios such as leisure and entertainment trips or shopping trips are not considered. The factors that influence travel chains are not addressed either, so the generalizability of the findings to other purposes cannot be guaranteed. The contextual study and travel chains will be considered in our next step study.

Finally, this paper does not address the long-term strategic effects of TDM policy mixes. A proper understanding of the mechanism linking policy design and corresponding influence inevitably requires the continuous integration of complementary quantitative research inputs.

6. Conclusions

This study provides an empirical analysis of the influence of the characteristics of the policy mix on individual mode choices in Beijing. Seven travel modes considering the role of seven traffic demand management policy instruments and their corresponding policy mixes applicable to Beijing was investigated.

One of the key findings of this manuscript is that combining policy instruments will lead to differentiated, context-specific policy performance. However, in the urban traffic system, different departments tend to release new TDM policy measures without carefully considering their combined effects with the existing measures of other departments. The 7 policy measures discussed in this article are all TDM policy measures that have been adopted or planned to be adopted in Beijing. Their combined effect did not show an encouraging picture.

It is also worth noticing that with this analysis framework, the counterproductive policy pairs as well as complementary policy pairs (policy buddies), can be clearly identified and used to assist more effective TDM policy portfolio design for stakeholders.

As mentioned in section 5.3, the proposed research still has limitations. This result is only based on the survey data. Since perception of commuters may vary depending on different real-life scenarios, their behavior could be more complicated. It should also be noted that the survey bias cannot be avoided due to more female respondents in this study. Therefore, adopting the analysis framework in field experiment scenarios with more balanced sample setting will be our next approach to avoid this bias in stated preference context.

Sensitivity to most of the policy attributes is likely to differ based on individual characteristics and the trip context that each respondent has in mind during the SP experiments. This study mainly focused on interactions between policies but did not analyze the heterogeneity in sensitivity to those policies; this will be the subject of a future study. The next steps of this study will also involve field experiments and further complementary policy package design with quantitative empirical analysis.

Author statement

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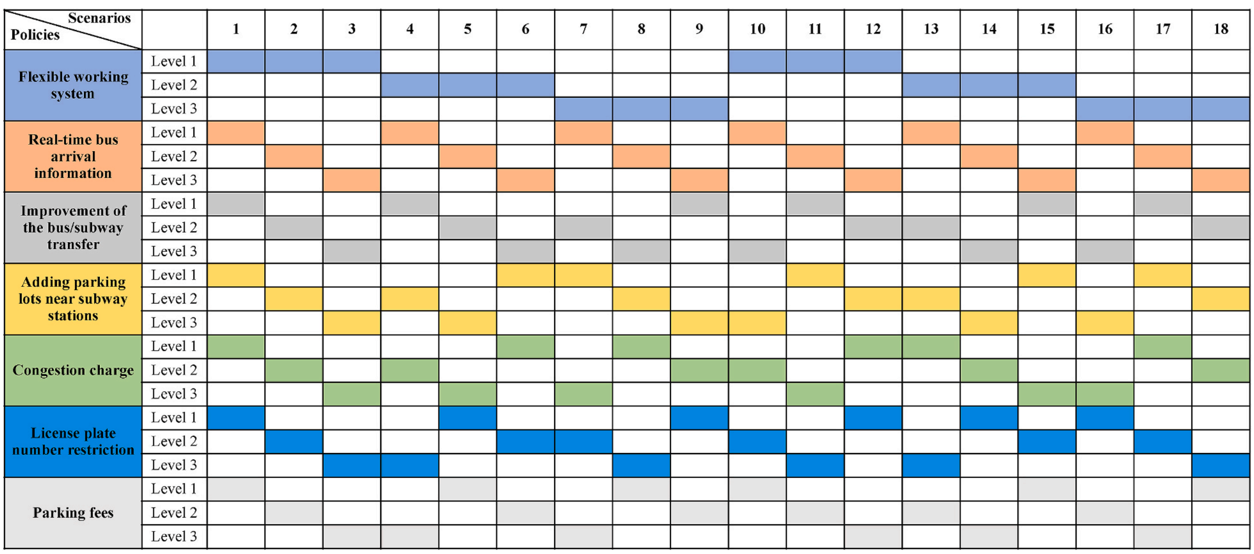
Annex.

A.1 Scenarios setting and corresponding policy instrument levels



A.2 Policy instrument level design

Policy	Design detail	Reference
Flexible work (x1h1, x1wh)	Since the most restricted situation and the most relaxed situation of working flexibility are no flexibility and work at home, these two situations have been set as the level 1 and level 3 of flexible working system separately. The 1-h working flexibility has been set as level 2.	(none)
Real-time bus arrival information (x2)	At the end of 2016, Beijing government has launched an APP named *Beijing Jiaotong*, which is used to provide real-time bus information. Most citizens found that the APP was useful and helpful with errors less than 1 min[1]. However, for some other cities, the results are not such satisfactory. The gap between the expected arrival time provided by the traffic APP and the real time could reach 10mins[2]. Hence, we used the forecast error less than 1 min as the most ideal level (Level 3) for this policy, error less than 10 min for level 2, and no such information as the base level (Level 1).	[1]https://news.163.com/16/1117/01/C61NDDQ9000187VI.html, Accessed 2021/03/31. [2]https://www.sohu.com/a/168525713_180466, Accessed 2021/03/31.
Improvement of the bus/subway transfer (x3)	Following Habibian and Kermanshah (2011), the percentage of transit time reduction has been used to reflect the improvement of the bus/subway transfer. Level 1 is no time saving, which was used to reflect the status quo. Level 2 and level 3 increase the time reduction percentage gradually.	Habibian & Kermanshah (2011)

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(*continued*)

Policy	Design detail	Reference
Adding parking lots near subway stations (x4)	The sharp contradiction between fast-growing vehicles and limited parking lots has been a serious problem for Beijing (Wang et al., 2016). Parking difficultly is then a hot topic being discussed by the citizens. In some central zones, drivers complained that searching for a parking space took them about 20 mins[1]. Hence, in this study, the searching time has been used as an important index to measure the construction level of park and ride parking lots. 20 mins in looking for parking space has been used as the base level to reflect the current serious condition. The searching time for Level 2 and Level 3 gradually decrease by two times of the previous level.	[1]https://www.xiaohongshu.com/discovery/item/5fe08377000000000101df74, Accessed 2021/03/31. Wang Yan-ling*, Wang Xin, Zhang Ming-chun. (2016). Current Situation and Analysis of Parking Problem in Beijing. Procedia Engineering. 137, 777–785.
Congestion charge (x5)	We used the current highway toll fee for sedan cars in China as a base level (Level 1) for road congestion charge, which equals 0.5 Yuan per km. Following the setting of Ubbels and Verhoef (2005), the other two levels gradually increase by two times of the previous level. Hence, Level 2 and Level 3 have been set to 1 Yuan per car per km and 2 Yuan per car per km separately.	Barry Ubbels, & Erik T. Verhoef. (2005). Behavioural responses to road pricing. Empirical results from a survey among Dutch car owners. European Transport\Trasporti Europei 31 (31):101–117.
Traffic restrictions based on the last digit of license plate numbers (x6)	Chinese government implemented the driving restriction policy since 2008. During the 2008 Olympics, Beijing banned half of the vehicles per day, i.e., five digits were restricted. After the Olympics game, the restriction was then relaxed by banning two digits per day (Guo et al., 2017). Hence, the level 2 and 3 for the driving restriction has been designed based on the number of vehicles restricted, which are the restriction of two digits per day and restriction of five digits per day. Then, no restriction has been set to the most relax level of this policy (Level 1).	Yizhen Gu, Elizabeth Deakin, Ying Long (2017). The Effects of Driving Re- strictions on Travel Behavior Evidence from Beijing, Journal of Urban Economics, 102: 106–122.
Parking fee (x7)	From 2010, Beijing government has increased the parking fee in the central city. The on-street parking fee for 13 key areas (inside the fourth ring road) has rose to a maximum of 20 yuan per hour1. Hence, we set 20 yuan per hour as the base level, and gradually increased the parking fee for following levels.	[1]http://eladies.sina.com.cn/shopping/2010/0421/1815986858.shtml?from=wap, Accessed 2021/03/31.

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