Environmental behaviour and choice of sustainable travel mode in urban areas: comparative evidence from commuters in Asian cities

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Abstract

Promoting pro-environmental travel modes is an important strategy for sustainable transportation. Previous studies have shown a positive relationship between environmental awareness and environmentally friendly travel modes, but very few studies have considered pro-environmental behaviour and choice of travel mode, particularly in the context of non-Western countries. This study examines the impact of pro-environmental behaviour on the choice of commuting mode in Tokyo, Beijing, Shanghai and Singapore using original survey data. We use the Multiple Indicator Multiple Cause model to construct latent variables of environmentally friendly behaviours. The multinomial logistic regression results indicate that 1) pro-environmental activities and commuting mode choice are unrelated in Tokyo and Singapore, 2) recycling and energy-savings activities are positively related to commuting by bicycle/on foot in Beijing, and 3) participants in organized pro-environmental activities are less likely to use pro-environmental commuting modes in Beijing and Shanghai. The results provide supporting evidence of the habit discontinuity hypothesis and suggest a possible substitution effect between environmentally friendly travel mode choice and other environmental activities.

Keywords: Sustainable transportation; environmental behaviour; travel demand; commuting; Asian cities

1. Introduction

Understanding transportation mode choices is important for policy makers and transportation planners to assess, forecast and control travel demand and supply. Recent studies have increasingly highlighted the importance of sustainable transportation, as rapid urbanization has increased the severity of road congestion and air pollution (Gardner and Abraham, 2010; Lind et al., 2015). The shift to environmentally friendly transportation is one of the main countermeasures to environmental damage, and the viability and strategy of such a shift have been widely discussed (e.g., Schneider, 2013; Kim and Ulfarsson, 2008; Tamaki et al., 2019; Nakamura et al., 2019). Previous research findings suggest that understanding people's travel mode choices is crucial for predicting the effectiveness of policies on transportation and environmental sustainability as well as the impact of new technological developments in related fields.

In these days, researchers have paid attention to how to realize sustainability in supply chain management (Pagell and Shevchenko, 2014; Marshall et al., 2015; Irani et al., 2017; Dubey et al., 2017; Hong et al., 2018). Lee (2011) suggested that reducing Scope 3 emissions is more cost-effective for companies than reduction in direct or electricity related indirect emissions. Here Scope 3 emissions are all indirect emissions that occur in the value chain of the reporting company, including both upstream and downstream emissions. Harangozo and Szigeti (2017) mentioned that Scope 3 emissions are frequently ignored by companies despite the findings that Scope 3 occupies the largest share of corporate carbon footprints (Stein and Khare, 2009; Matthews et al., 2008).

The modal shift to environmentally friendly travel modes are also related to supply chain management, especially in terms of employees' commuting from residence to workplace. According to the Greenhouse Gas Protocol (World Business Council For

Sustainable Development and World Resources Institute, 2011), Scope 3 includes the emissions from employee commuting. They suggested "create disincentives for commuting by car" and "provide incentives for use of public transit, bicycling, carpooling, etc." as actions to reduce Scope 3 emissions. Indeed, as noted by Onat et al. (2014), employees' commuting affects the amount of Scope 3 emission most substantially. Therefore, companies may have capacity to significantly reduce emission through supporting and promoting employees' greener commutes.

Previous studies have shown that travel time, cost, and socio-demographic variables affect transportation mode choices (Ben-Akiva and Lerman, 1985; Ben-Akiva and Bierlaire, 1999). More recent studies have found statistically significant effects of subjective attitudes and perceptions (Anable, 2005; Hunecke et al., 2010) and have examined the impact of perceptions of ride comfort, convenience, flexibility, safety and security on travel mode choice (e.g., Morikawa et al., 2002; Temme et al., 2008; Daly et al., 2012). In addition, research has also found that environmental awareness is a significant subjective determinant of travel mode choice. Empirical evidence suggests that individuals with high environmental awareness are systematically more likely to choose environmentally friendly travel modes: public transportation, walking and cycling (Schwanen and Mokhtarian 2005; Johansson et al., 2006; Gardner and Abraham, 2010; Klöckner and Blöbaum, 2010; Lind et al., 2015).[1]

Nevertheless, most of empirical evidence on subjective environmental measures and travel mode choice are based on data from developed Western countries (Gardner and Abraham, 2008). Hence, in this study, we analyze the relationships between pro-environmental behaviours and commuting mode in four major Asian cities—Tokyo, Beijing, Shanghai and Singapore—based on an original survey conducted in 2015-2016.

We consider energy-savings activities and participation in environmentally friendly activities organized by the government, corporations or other organizations in addition to recycling behaviour to test the relationship between environmental actions and travel mode choice. The results provide comparative evidence with both previous studies' examinations that have only focused on environmental attitudes towards travel. For the target cities, we elucidate the impacts of differences in the development of transportation systems and environmental preferences on environmentally friendly travel behaviour. We use the Multiple Indicator Multiple Cause (MIMIC) model introduced by Bollen (1989) to construct latent variables of environmental friendliness from subjective indicators, and we use multinomial logistic (MNL) regression to analyze the impact of mode choice factors on three commuting modes: car, public transportation (PT), and bicycle/on foot, or active travel (AT).

Cross-city comparisons enable us to assess possible variations in the relationships and to examine theoretical frameworks that may affect the linkage between environmental preferences and travel mode choice. Travel behaviour is determined by region-specific social and moral norms that heavily depend on the social context (Bamberg et al., 2007; Chan and Bishop, 2013). Hence, we should proceed with caution when generalizing previous results to the target cities. The implications of the 'habit discontinuity hypothesis' and the 'self-activation hypothesis' suggest possible variations between cities in developed countries and those in developing countries. Klöckner and Matthies (2004) indicated that 'habit' is a significant predictor of mode choice, and when habits are disrupted by changes in the environment where the behaviour takes place, environmental concerns become relatively more prominent determinants of travel mode choice (Verplanken & Wood, 2006; Wood et al., 2005; Verplanken et al., 2008). The 'self-activation hypothesis' suggests that disruptions of habits caused by a changing environment can act as a trigger to activate certain values contained in individuals' 'self-concept', and these activated values in turn affect behaviour (Utz, 2004; Verplanken & Holland, 2002).

We examine whether there is difference between Tokyo and Singapore, which have relatively little habit discontinuity in terms of changes in transportation infrastructure and in the availability of travel modes compared to Beijing and Shanghai, where the transportation environments are rapidly changing. Furthermore, even if we find statistically significant relationships between pro-environmental travel mode choice and other environmental activities, the direction of the relationship may not necessarily be positive. Johansson et al. (2006) have suggested that pro-environmental travel mode choice and other environmental behaviours may act as either complements or substitutes of each other.

The rest of this paper is structured as follows. Section 2 describes the survey data, and section 3 explains the method used in the empirical analysis. Section 4 discusses the results and concludes.

2. Data

We use original data from an Internet survey that we conducted in 2015–2016 in Japan, China and Singapore. This survey was conducted with the purpose of investigating the relationship between environmental awareness, environmental behaviour, travel behaviour and satisfaction with various factors surrounding respondents. The sample were randomly collected through internet while considering national gender and age distributions for each country.[2] From the data collected by the survey, we extracted the workers in four major Asian cities: Tokyo, Beijing, Shanghai and Singapore. According to the Global Power City Index 2016 (The Mori Memorial Foundation, 2016), these cities are ranked in the top 20 worldwide in terms of their economy, research and development, cultural interaction, livability, environment and accessibility. The sample comprises 760, 1,656, 1,628, and 394 commuters in Tokyo, Beijing, Shanghai, and Singapore, respectively. As travel behaviour seems to be different by transportation environment, we selected transit-oriented cities: Tokyo and Singapore, and car-oriented cities: Beijing and Shanghai for comparison.

The questionnaire included several categories of questions: commuting mode, socioeconomic characteristics, and various subjective factors, including environmentally friendly behaviour and activities.

This study focuses on three categories of travel mode: (1) car, (2) PT, and (3) AT. Respondents were asked to select all the travel modes they use for commuting: car, motorcycle, bicycle, bus, train, on foot and other. We excluded motorcycle commuters because of the limited number of observations. We categorized respondents as car users if they only use a car for commuting and if they use a car as their main commuting mode if they selected multiple modes. Train and/or bus commuters are classified as PT users. Similarly, we combined the respondents who selected bicycle and/or walking and categorized them as AT users. Table 1 describes the prevalence of the different commuting mode groups in the examined cities and shows that the distributions significantly vary across cities. PT is the most common commuting mode in Tokyo and Singapore, while car travel is the most common mode in Beijing and in Shanghai. AT commuters constitute the smallest share in all cities except in Tokyo, where cars have the smallest share.

Table 1. The distribution of three groups of commutes modes.

	Car	PT	AT	Total
Tokyo	52 (6.8%)	607 (79.9%)	101 (13.3%)	760
Beijing	835 (50.4%)	587 (35.5%)	234 (14.1%)	1,656
Shanghai	871 (53.5%)	624 (38.3%)	133 (8.2%)	1,628
Singapore	132 (33.5%)	247 (62.7%)	15 (3.8%)	394

Respondents were asked to select all actions that they have taken or participated in out of thirteen available options (see Table A.1 for the details). Table 2 shows the share of respondents who selected each action. We use these responses as indicator variables of environmental behaviour in order to construct latent variables of environmental preferences. In addition to environmental perception variables, we control for several individual characteristics. Table A.2 provides summary statistics for all the explanatory variables.

Table 2. Percentages of respondents who had taken or participated in these actions.

	Tokyo	Beijing	Shanghai	Singapore
Recycling/sorting (y_1)	76.1%	42.3%	41.9%	67.3%
Cleaning (y_2)	16.2%	35.9%	28.0%	21.6%
Energy saving (y_3)	49.7%	58.2%	52.8%	72.8%
Recycled goods (y_4)	22.5%	41.5%	40.4%	21.8%
Energy-saving goods (y_5)	28.8%	56.0%	58.4%	49.5%
Government (y_6)	3.2%	20.2%	19.6%	19.0%
Corporations (y_7)	6.3%	12.3%	14.5%	12.9%
International (y_8)	1.2%	7.6%	14.8%	9.1%
Education (y_9)	3.7%	20.8%	22.5%	20.6%
Animal protection (y_{10})	3.2%	17.4%	17.4%	21.8%
Forest protection (y_{11})	2.8%	16.7%	19.7%	12.9%
Policy (y_{12})	1.4%	13.3%	13.3%	16.8%
Meetings (y_{13})	0.5%	4.0%	2.5%	5.8%

3. Empirical analysis

Methodological advances in the 1970s led to the development of disaggregate behavioural models based on discrete choice analysis methods, and these powerful tools are used to analyze travel mode choices and transportation demand management at the individual level (McFadden, 1973; Domencich and McFadden, 1975; McFadden, 2000). The hypothesis underlying the choice model is that an individual selects the mode that provides the highest utility among a set of alternatives. In conventional empirical analyses of mode choice, this utility is a function of modal attributes, such as travel time and cost, and socio-demographic variables, such as income, gender and the number of household members (Ben-Akiva and Lerman, 1985). The hybrid choice model additionally includes travelers' subjective perceptions and their attitudes toward travel modes as determinants in addition to the objective factors that are included in conventional discrete choice models (Ben-Akiva et al., 2002a).

The simplest approach to incorporating subjective dimensions into a discrete choice model is to directly include subjective explanatory variables (e.g., Harris and Keane, 1998). However, recent related studies have introduced latent variables, which incorporate unobservable individual preferences underlying the indicators based on individuals' responses to questions about their environmental attitudes and behaviour. Some studies have used factor analysis to construct latent variables (e.g., Schwanen and Mokhtarian 2005), and others have used the MIMIC model, which is considered a more suitable approach than factor analysis for incorporating people's attitudes and perceptions (Ben-Akiva et al., 2002b).

Fig. 1 describes the framework of integrated choice and latent variable model (Ben-Akiva et al., 1999). The ellipses in the figure refer to latent variables, and the rectangles refer to observable variables. We describe the MIMIC model, which we use to construct latent variables of pro-environmental behaviour, and present the results. Then, we present the choice model equation and the results of the MNL estimations.

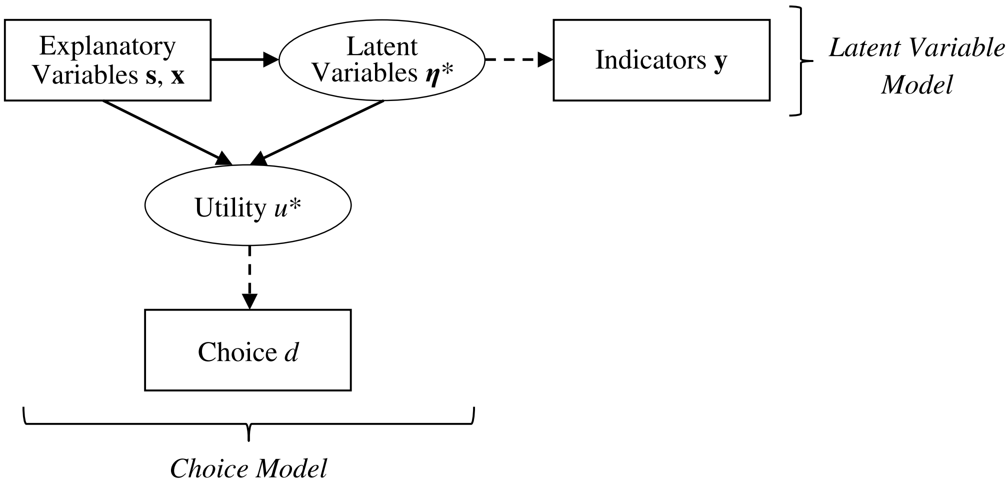

Figure 1. Integrated choice and latent variable model (Ben-Akiva et al., 1999).

3.1 Integrated Choice and MIMIC model

Johansson et al. (2006) found that subjective attitudes and personality traits had statistically significant effects and improved the explanatory power of the choice model. Several subsequent studies analyzed the impact of subjective latent factors constructed using a MIMIC model (Yáñez et al., 2010; Raveau et al., 2012; Paulssen et al., 2014; Fernández-Heredia et al., 2016). We use the MIMIC model to estimate the latent variables underlying the indicator variables of environmental behaviour. This model simultaneously estimates two equations. One is a *structural equation*,

$$\boldsymbol{\eta}^* = \boldsymbol{\Gamma}\boldsymbol{s} + \boldsymbol{\nu} \tag{1}$$

where the latent variables $\boldsymbol{\eta}^*$ are explained by characteristics $\boldsymbol{s}$ of individuals and alternatives, $\boldsymbol{\Gamma}$ is a matrix of unknown parameters, and $\boldsymbol{\nu}$ is a vector of normally distributed disturbances. The other is a *measurement equation*,

$$\boldsymbol{y} = \boldsymbol{\Lambda}\boldsymbol{\eta}^* + \boldsymbol{\zeta} \tag{2}$$

where the latent variables explain the perception indicators $\boldsymbol{y}$, $\boldsymbol{\Lambda}$ is a matrix of unknown parameters, and $\boldsymbol{\zeta}$ is a vector of normally distributed disturbances.

The sequential method and the simultaneous method can both be used to estimate the effect of latent variable on mode choices, but we use the sequential method because of its simplicity. The utility function of the discrete choice model includes latent variables constructed using the MIMIC model:

$$u_j^* = \boldsymbol{\theta}_j \boldsymbol{x} + \boldsymbol{\beta}_j \boldsymbol{\eta}^* + \varepsilon_j \tag{3}$$

where u_j^* is latent utility for mode j ($j \in J$), $\boldsymbol{x}$ is a vector of observable explanatory variables, $\boldsymbol{\theta}_j$ and $\boldsymbol{\beta}_j$ are arrays of unknown parameters, and ε_j is a random component of utility. The equations of the observable choice are also needed:

$$d_j = \begin{cases} 1 \ \text{ if } u_j^* \geq u_k^*, \forall k \in J \\ 0 \ \text{ otherwise} \end{cases} \tag{4}$$

where d_j is the dummy variables of choosing mode j. A commuter chooses the mode that maximizes his/her utility.

3.2 The results of the MIMIC model

Many studies that applied to MIMIC model have hypothesized that the latent awareness towards modal choice is determined from sociodemographic characteristics such as age, gender and household income. We followed these previous studies and set the specification of structural equation (1) based on Johansson et al. (2006):

$$\begin{aligned} \eta_{li}^* &= \gamma_{l1}\text{Female}_i + \gamma_{l2}\text{Age}_i + \gamma_{l3}\ln(\text{Income}_i) + \gamma_{l4}\text{Education}_i \\ &+ \gamma_{l5}\text{Child}_i + \gamma_{l6}\text{House}_i + \nu_{li}, \end{aligned} \tag{5}$$

$$l = \text{daily action at home, external activity participation,}$$

where i refers to the respondents. Gender, age, household income, educational attainment, the number of children and residential type are the determinants of latent variables.

Tables 3 and 4 show the estimation results of the measurement equations and the structural equations of the MIMIC model, respectively. According to the results of the exploratory and confirmatory factor analysis, five indicators that are mainly related to environmentally friendly actions that can be taken at home have high loadings on the latent variable η_{home}. Eight indicators that are related to participation in pro-environmental activities organized by the government, corporations or other organizations have high loadings on the latent variable η_{external}.

Table 4 describes the characteristics of environmentally friendly commuters. Females in Tokyo and Singapore are more likely to engage in the pro-environmental actions contained in η_{home}, while in Shanghai, males are more likely to do so. Moreover, male commuters in Beijing are more likely to participate in environmental activities than female commuters. Although older commuters are more likely to do take environmental action in Tokyo and Singapore, younger commuters are more likely to do so in Shanghai. Higher household income increases the propensity to take pro-environmental action, except among Beijing commuters. People with higher education are more likely to take environmental friendly action in Beijing and Shanghai. Commuters with children are also likely to take environmentally friendly action, except in the case of Beijing, where having children decreases the likelihood of engaging in the actions associated with η_{home}. With the exception of commuters in Singapore, commuters residing in a rented apartment/mansion are more likely to engage in the pro-environmental actions associated with η_{home} but are less likely to participate in the environmental activities associated with $\eta_{external}$. These differences across the cities may be due to differences in people's lifestyles and personalities.

Table 3. MIMIC model results of measurement equations.

Indicator variable	Latent variables							
	Tokyo		Beijing		Shanghai		Singapore	
	η_{home}	$\eta_{external}$	η_{home}	$\eta_{external}$	η_{home}	$\eta_{external}$	η_{home}	$\eta_{external}$
Recycling/sorting (y_1)	1		1		1		1	
Cleaning (y_2)	0.63 (6.93)		0.37 (4.14)		0.31 (6.01)			1
Energy saving (y_3)	1.32 (9.62)		1.05 (8.10)		0.91 (12.1)		1.31 (5.37)	
Recycled goods (y_4)	0.85 (6.84)		1.05 (8.02)		0.58 (8.20)			1.23 (6.75)
Energy-saving goods (y_5)	1.19 (7.81)		1.08 (7.93)		0.61 (8.38)		1.49 (4.85)	
Government (y_6)		1		1		1		1.47 (7.53)
Corporations (y_7)		0.77 (7.92)		0.72 (9.41)		0.81 (12.8)		1.18 (7.25)
International (y_8)		0.47 (10.5)		0.57 (9.48)		0.77 (12.0)		1.05 (7.42)
Education (y_9)		0.59 (8.09)		1.23 (11.3)		1.16 (13.9)		1.48 (7.41)
Animal protection (y_{10})		0.61 (8.24)		1.11 (10.9)		1.09 (14.2)		1.19 (6.54)
Forest protection (y_{11})		0.50 (7.32)		1.21 (11.3)		1.03 (13.4)		1.32 (7.52)
Policy (y_{12})		0.42 (8.77)		1.10 (11.7)		1.05 (15.7)		1.44 (7.58)
Meetings (y_{13})		0.07 (2.58)		0.53 (10.7)		0.24 (9.43)		0.67 (6.71)

Note: Maximum likelihood estimator. *z*-statistics in parentheses. Variable definitions are given in Table A.1 in Appendix.

Table 4. MIMIC model results of structural equations.

		Female	Age	ln(income)	Education	Child	Apartment (own)	House (rent)	House (own)	Other housing
Tokyo	η_{home}	0.106 (4.81)	0.004 (3.95)	0.043 (2.61)	–	0.023 (2.16)	–	–	–	–
	$\eta_{external}$	–	–	–	–	–	–	0.162 (4.00)	–	–
Beijing	η_{home}	–	–	0.068 (5.82)	0.011 (2.66)	−0.039 (−2.63)	−0.145 (−4.85)	−0.316 (−5.69)	−0.184 (−5.08)	–
	$\eta_{external}$	−0.028 (−2.76)	–	−0.014 (−2.07)	0.009 (2.95)	0.057 (5.46)	0.067 (3.47)	0.083 (2.43)	0.103 (4.26)	0.146 (3.08)
Shanghai	η_{home}	−0.100 (−5.20)	−0.003 (−2.92)	0.065 (4.49)	0.029 (6.55)	–	–	−0.209 (−2.44)	–	–
	$\eta_{external}$	–	−0.002 (−3.33)	0.041 (4.69)	0.010 (4.22)	0.051 (4.23)	–	–	0.068 (2.00)	–
Singapore	η_{home}	0.068 (2.35)	0.006 (3.82)	–	–	–	–	–	–	–
	$\eta_{external}$	–	–	–	–	–	−0.097 (−2.20)	−0.119 (−1.70)	−0.110 (−2.35)	−0.183 (−3.14)

Note: Maximum likelihood estimator. *z*-statistics in parentheses. Only significant coefficients are shown.

3.3 Choice of commuting mode

We then include the latent variable estimate with the MIMIC model in the discrete choice model, as in the following equation:

$$u_{ij}^* = \beta_{j1}\eta_{\mathrm{home},i}^* + \beta_{j2}\eta_{\mathrm{external},i}^* + \boldsymbol{\theta}_j \boldsymbol{X}_i + \varepsilon_{ij}$$
$$j = \text{car, PT, active travel (bicycle/ on foot).} \tag{6}$$

We use an MNL model to estimate equation (6) for each city. The MNL model is the most common method for estimating mode choice models (e.g., Bueno et al., 2017). The dependent variable is a categorical variable of three commuting modes: car, PT, and AT. The main explanatory variables are two latent variables, η_{home} and η_{external}, that measure the propensity to take pro-environmental action. We also control the set of variables, $\boldsymbol{X}$, which consists of gender, age, log (household income), years of education, number of children, type of dwelling, marital status, type of industry, factors of personality and the area dummies of residences. We calculate the marginal effect from the coefficients of the explanatory variables of the model in order to estimate the effect on the predicted probabilities for choosing each commuting mode.

3.4 The results of the choice model

Table 5 shows the estimated coefficients from the MNL estimation of the commute choice model in each city. The MNL coefficients indicate the effect on the relative likelihood of choosing a mode compared with a baseline category, which is a car in this analysis. Thus, the coefficients indicate the likelihood of choosing PT or AT relative to the likelihood of choosing to commute via car. Specification (1) is the baseline model that includes socioeconomic variables as predictors, and specification (2) adds two latent variables, η_{home} and η_{external}, to the baseline model. Pseudo R^2 is a goodness-of-fit index for an econometric model with a limited dependent variable such as a categorical variable. As a Pseudo R^2 for our model, we used McFadden's R^2, which ranges from 0 to 1 and is the most frequently used in empirical studies (Veall and Zimmermann, 1996).

The results of specification (2) indicate that the latent variables are statistically significant for Beijing and Shanghai commuters but not for Tokyo and Singapore commuters. η_{home} has a significant impact on the likelihood of choosing AT among commuters in Beijing. The result also shows that the preferences for engaging in the pro-environmental actions associated with η_{home} increase the likelihood of choosing AT over car travel. A one-standard-deviation increase in η_{home} increases the likelihood of choosing AT over car travel by 24.8% among Beijing commuters. In contrast, η_{external} is positively related to choosing car travel over PT and AT. A one-standard-deviation increase in η_{external} decreases the likelihood of choosing PT over car travel by 13.6% in Beijing and 24.9% in Shanghai, and it decreases the likelihood of choosing AT over car travel by 46.1% in Beijing and 35.0% in Shanghai. Thus, participation in environmental activities organized by external organizations decreases the likelihood of choosing environmentally friendly travel modes over cars.

The estimators of specification (1) describe the relationships between commuting mode choice and individuals' socioeconomic characteristics by city. Household income, education, gender and residence type dummies are significant predictors of commuting choice in all cities, while the number of children, age, and marital status are significant in some cities.

Table 5. MNL coefficients estimates (car as baseline commuting mode).

	Tokyo		Beijing		Shanghai		Singapore	
VARIABLES	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
PT								
η_{home}		1.022		-0.0947		0.530		-0.128
		(0.957)		(-0.185)		(1.560)		(-0.131)
η_{external}		-0.270		-1.079**		-1.696***		-0.390
		(-0.185)		(-2.231)		(-3.914)		(-0.474)
Female	0.408	0.268	0.442***	0.409***	0.233*	0.305**	0.416	0.425
	(1.065)	(0.658)	(3.543)	(3.251)	(1.879)	(2.369)	(1.559)	(1.547)
Age	0.016	0.013	0.020***	0.020***	0.002	0.001	-0.006	-0.005
	(0.979)	(0.798)	(3.008)	(2.890)	(0.362)	(0.125)	(-0.417)	(-0.306)
ln(Household income)	-0.105	-0.137	-0.548***	-0.578***	-0.608***	-0.583***	-0.896***	-0.898***
	(-0.313)	(-0.401)	(-5.877)	(-5.854)	(-5.649)	(-5.334)	(-3.705)	(-3.712)
Education	0.209**	0.205**	-0.137***	-0.128***	-0.215***	-0.211***	-0.055	-0.053
	(2.234)	(2.207)	(-3.709)	(-3.416)	(-6.579)	(-6.359)	(-0.882)	(-0.842)
Child	-0.250	-0.259	-0.519***	-0.455***	-0.382**	-0.318**	0.114	0.123
	(-1.429)	(-1.462)	(-3.745)	(-3.163)	(-2.500)	(-2.066)	(0.765)	(0.813)
Apart (own)	0.827*	0.848*	-1.752***	-1.679***	-0.563*	-0.552*	-1.606**	-1.696**
	(1.781)	(1.809)	(-6.506)	(-5.962)	(-1.702)	(-1.662)	(-2.174)	(-2.227)
House (rent)	13.46	13.42	-0.834*	-0.770	-0.095	0.118	-0.473	-0.576
	(0.0158)	(0.0160)	(-1.884)	(-1.630)	(-0.159)	(0.195)	(-0.431)	(-0.513)
House (own)	-0.214	-0.226	-1.979***	-1.878***	-0.967**	-0.855**	-1.517*	-1.609**
	(-0.493)	(-0.518)	(-6.244)	(-5.609)	(-2.375)	(-2.089)	(-1.955)	(-2.012)
Other house	14.04	13.81	-0.572	-0.365	-0.418	-0.328	-1.150	-1.272
	(0.0141)	(0.0138)	(-0.918)	(-0.575)	(-0.315)	(-0.238)	(-1.269)	(-1.355)
Single	1.289**	1.325**	0.195	0.213	0.695***	0.698***	0.484	0.488
	(2.250)	(2.300)	(0.752)	(0.821)	(2.722)	(2.718)	(1.319)	(1.326)
Separated/Divorced	-0.187	-0.193	-0.806	-0.727	0.325	0.306	-0.260	-0.278
	(-0.296)	(-0.305)	(-1.200)	(-1.067)	(0.615)	(0.580)	(-0.438)	(-0.466)
Constant	0.428	0.361	8.022***	8.245***	9.345***	9.424***	13.25***	13.39***
	(0.104)	(0.0876)	(7.096)	(7.220)	(7.539)	(7.570)	(4.463)	(4.468)
AT								
η_{home}		1.658		1.538**		0.131		1.782
		(1.332)		(1.996)		(0.220)		(0.619)
η_{external}		-1.370		-4.583***		-2.553***		-2.801
		(-0.672)		(-5.097)		(-2.922)		(-0.907)
Female	0.893**	0.675	0.098	-0.009	-0.242	-0.194	0.071	-0.056
	(2.042)	(1.450)	(0.550)	(-0.0497)	(-1.117)	(-0.877)	(0.0903)	(-0.0685)
Age	0.001	-0.004	0.009	0.009	0.007	0.003	-0.030	-0.027
	(0.0462)	(-0.197)	(0.914)	(0.887)	(0.552)	(0.272)	(-0.777)	(-0.669)
ln(Household income)	-0.935**	-0.970**	-0.417***	-0.636***	-0.748***	-0.693***	-1.550**	-1.586**
	(-2.507)	(-2.558)	(-3.290)	(-4.590)	(-4.892)	(-4.461)	(-2.395)	(-2.380)
Education	0.097	0.094	-0.090*	-0.073	-0.215***	-0.198***	-0.423***	-0.415***
	(0.897)	(0.873)	(-1.664)	(-1.315)	(-4.322)	(-3.826)	(-2.719)	(-2.696)
Child	0.033	0.025	-0.365*	-0.048	0.020	0.108	0.893**	0.918**
	(0.156)	(0.117)	(-1.872)	(-0.233)	(0.0828)	(0.446)	(2.058)	(2.037)
Apart (own)	0.688	0.736	-0.885**	-0.486	-0.523	-0.511	-1.776	-1.937
	(1.242)	(1.317)	(-2.264)	(-1.211)	(-1.043)	(-1.016)	(-0.956)	(-0.970)
House (rent)	13.76	13.84	-0.451	0.300	0.768	0.992	-17.90	-17.01
	(0.0162)	(0.0165)	(-0.772)	(0.479)	(0.974)	(1.238)	(-0.0071)	(-0.0111)
House (own)	0.675	0.668	-1.456***	-0.907*	0.319	0.488	-2.099	-2.214
	(1.327)	(1.306)	(-3.003)	(-1.796)	(0.555)	(0.842)	(-1.101)	(-1.066)
Other house	16.07	15.79	-0.450	0.133	1.904	1.980	-2.780	-2.924
	(0.0161)	(0.0158)	(-0.466)	(0.137)	(1.374)	(1.379)	(-1.263)	(-1.291)
Single	1.355**	1.418**	-0.575	-0.448	1.182***	1.193***	1.373	1.527
	(2.109)	(2.190)	(-1.396)	(-1.074)	(2.963)	(2.967)	(1.172)	(1.257)
Separated	0.005	-0.011	-0.556	-0.351	-2.506*	-2.620*	1.764	1.834

	(0.00753)	(-0.0153)	(-0.621)	(-0.396)	(-1.863)	(-1.925)	(1.460)	(1.505)
Constant	9.521**	9.308**	4.733***	5.183***	8.099***	8.540***	19.13***	19.00***
	(2.081)	(2.015)	(3.011)	(3.271)	(4.444)	(4.621)	(2.780)	(2.688)
Observations	760		1,656		1,628		394	
Pseudo R^2	0.156	0.159	0.142	0.154	0.190	0.198	0.214	0.216

Note: *z*-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All specifications include type of industry, factors of respondent's personality and the area dummies.

Table 6 shows the results of estimated marginal effects, which are calculated from the coefficients in Table 5. The value of a marginal effect can be interpreted as the influence on the predicted probabilities of commuters choosing each category of commuting mode. For cases in which the coefficients of latent variables are statistically significant, we calculate the average impacts of the latent variables for Beijing and Shanghai commuters; Table 7 shows the results. In Beijing, compared with commuters with $\eta_{\text{home}}=0$, commuters with an average value of η_{home} are 11.0% more likely to choose AT, and those with an average value of η_{external} are 3.2% less likely to choose AT. Nevertheless, the impact of a one-standard-deviation increase in the latent variables is larger for η_{external} than for η_{home}.

In terms of the effects of control variables, the results of marginal effects indicate that commuters with a higher household income and more years of education are more likely to commute by PT in Tokyo, although household income does not have a significant coefficient on choosing PT over car travel despite the significant impact of household income on the likelihood of choosing a car as a commuting mode in the other cities. This result may imply that upper-class commuters in Tokyo do not think of a car as a symbol and prefer to use PT, which is a convenient, cost-saving and highly developed travel mode.

Table 6. Choice model results: MNL marginal effect estimates.

	Tokyo		Beijing		Shanghai		Singapore	
VARIABLES	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Car								
η_{home}		-0.063		-0.071		-0.086		0.007
		(-1.07)		(-0.71)		(-1.43)		(0.04)
$\eta_{external}$		0.025		0.423***		0.335***		0.090
		(0.31)		(4.40)		(4.48)		(0.61)
Female	-0.027	-0.019	-0.074***	-0.063***	-0.029	-0.041*	-0.072	-0.072
	(-1.29)	(-0.84)	(-3.08)	(-2.60)	(-1.33)	(-1.84)	(-1.52)	(-1.49)
Age	-0.001	-0.001	-0.004***	-0.004***	-0.001	0.000	0.001	0.001
	(-0.83)	(-0.63)	(-2.80)	(-2.70)	(-0.48)	(-0.19)	(0.50)	(0.38)
ln(Household income)	0.014	0.015	0.110***	0.125***	0.117***	0.110***	0.166***	0.167***
	(0.76)	(0.84)	(6.15)	(6.70)	(6.23)	(5.82)	(4.10)	(4.11)
Education	-0.011**	-0.010**	0.027***	0.024***	0.040***	0.039***	0.013	0.012
	(-2.04)	(-2.02)	(3.59)	(3.21)	(7.06)	(6.74)	(1.19)	(1.14)
Child	0.011	0.012	0.102***	0.073***	0.059**	0.046*	-0.027	-0.029
	(1.17)	(1.21)	(3.81)	(2.64)	(2.20)	(1.71)	(-1.04)	(-1.08)
Apartment (own)	-0.045*	-0.046*	0.324***	0.288***	0.103*	0.100*	0.289**	0.306**
	(-1.73)	(-1.77)	(5.90)	(5.08)	(1.72)	(1.68)	(2.22)	(2.28)
House (rent)	-0.752	-0.748	0.156*	0.103	-0.008	-0.047	0.235	0.242
	(-0.02)	(-0.02)	(1.72)	(1.08)	(-0.07)	(-0.44)	(0.01)	(0.02)
House (own)	0.003	0.004	0.392***	0.342***	0.142*	0.118	0.277**	0.293**
	(0.14)	(0.17)	(6.17)	(5.13)	(1.95)	(1.64)	(2.02)	(2.07)
Other house	-0.801	-0.784	0.115	0.049	0.010	-0.006	0.220	0.242
	(-0.01)	(-0.01)	(0.87)	(0.37)	(0.04)	(-0.03)	(1.37)	(1.45)
Single	-0.072**	-0.074**	-0.003	-0.008	-0.143***	-0.142***	-0.094	-0.096
	(-2.26)	(-2.31)	(-0.06)	(-0.15)	(-3.16)	(-3.15)	(-1.46)	(-1.48)
Separated/Divorced	0.009	0.009	0.158	0.132	0.022	0.028	0.029	0.032
	(0.25)	(0.26)	(1.22)	(1.03)	(0.22)	(0.28)	(0.28)	(0.30)
PT								
η_{home}		-0.012		-0.083		0.096		-0.057
		(-0.13)		(-0.86)		(1.57)		(-0.32)
$\eta_{external}$		0.089		-0.021		-0.231***		-0.022
		(0.54)		(-0.22)		(-2.86)		(-0.14)
Female	-0.026	-0.025	0.083***	0.081***	0.053**	0.065***	0.077	0.081
	(-0.82)	(-0.75)	(3.57)	(3.46)	(2.37)	(2.82)	(1.59)	(1.62)
Age	0.002	0.002	0.004***	0.003***	0.000	0.000	-0.001	0.000
	(1.49)	(1.50)	(2.88)	(2.76)	(0.19)	(0.04)	(-0.21)	(-0.13)
ln(Household income)	0.072***	0.071***	-0.091***	-0.087***	-0.090***	-0.086***	-0.141***	-0.141***
	(2.74)	(2.67)	(-5.46)	(-4.99)	(-5.05)	(-4.78)	(-3.40)	(-3.39)
Education	0.020**	0.020**	-0.023***	-0.022***	-0.034***	-0.033***	-0.003	-0.002
	(2.47)	(2.43)	(-3.47)	(-3.26)	(-6.19)	(-6.01)	(-0.23)	(-0.21)
Child	-0.038**	-0.038**	-0.087***	-0.088***	-0.074***	-0.064**	0.005	0.006
	(-2.29)	(-2.32)	(-3.38)	(-3.27)	(-2.70)	(-2.35)	(0.18)	(0.22)
Apartment (own)	0.051	0.049	-0.309***	-0.311***	-0.089	-0.087*	-0.271**	-0.285**
	(1.26)	(1.22)	(-6.93)	(-6.60)	(-1.58)	(-1.54)	(-2.10)	(-2.15)
House (rent)	0.592	0.579	-0.146*	-0.164**	-0.046	-0.013	0.243	0.204
	(0.02)	(0.01)	(-1.88)	(-1.97)	(-0.44)	(-0.13)	(0.01)	(0.01)
House (own)	-0.092**	-0.093**	-0.330***	-0.332***	-0.197***	-0.180***	-0.248*	-0.263*
	(-2.45)	(-2.47)	(-6.01)	(-5.69)	(-2.80)	(-2.57)	(-1.83)	(-1.88)
Other house	0.459	0.453	-0.094	-0.077	-0.148	-0.133	-0.166	-0.187
	(0.01)	(0.01)	(-0.85)	(-0.69)	(-0.68)	(-0.60)	(-1.04)	(-1.13)
Single	0.053	0.052	0.063	0.061	0.091**	0.090**	0.066	0.064
	(1.20)	(1.18)	(1.31)	(1.27)	(2.04)	(2.02)	(0.97)	(0.93)
Separated/Divorced	-0.026	-0.026	-0.136	-0.129	0.151	0.152	-0.082	-0.086
	(-0.50)	(-0.48)	(-1.07)	(-1.00)	(1.56)	(1.57)	(-0.76)	(-0.80)

AT								
η_{home}		0.074		0.154**		-0.011		0.050
		(0.94)		(2.14)		(-0.29)		(0.67)
$\eta_{external}$		-0.114		-0.402***		-0.104*		-0.068
		(-0.72)		(-4.73)		(-1.89)		(-0.84)
Female	0.053**	0.044	-0.009	-0.018	-0.024*	-0.023*	-0.006	-0.009
	(2.02)	(1.57)	(-0.51)	(-1.07)	(-1.80)	(-1.73)	(-0.28)	(-0.43)
Age	-0.001	-0.002	0.000	0.000	0.000	0.000	-0.001	-0.001
	(-1.12)	(-1.28)	(0.02)	(0.02)	(0.46)	(0.24)	(-0.70)	(-0.62)
ln(Household income)	-0.086***	-0.086***	-0.019	-0.038***	-0.027***	-0.024***	-0.025	-0.026
	(-4.07)	(-4.05)	(-1.62)	(-3.08)	(-3.18)	(-2.79)	(-1.52)	(-1.53)
Education	-0.009	-0.009	-0.003	-0.002	-0.006**	-0.005*	-0.010**	-0.010**
	(-1.37)	(-1.34)	(-0.65)	(-0.36)	(-2.24)	(-1.77)	(-2.58)	(-2.58)
Child	0.026*	0.026*	-0.015	0.014	0.015	0.018	0.022*	0.022*
	(1.83)	(1.83)	(-0.80)	(0.75)	(1.02)	(1.25)	(1.88)	(1.85)
Apartment (own)	-0.006	-0.003	-0.015	0.023	-0.014	-0.013	-0.018	-0.021
	(-0.18)	(-0.10)	(-0.44)	(0.67)	(-0.48)	(-0.46)	(-0.39)	(-0.41)
House (rent)	0.160	0.169	-0.010	0.061	0.053	0.060	-0.478	-0.447
	(0.02)	(0.02)	(-0.20)	(1.13)	(1.22)	(1.35)	(-0.01)	(-0.01)
House (own)	0.089***	0.089***	-0.063	-0.010	0.055*	0.062*	-0.029	-0.030
	(2.73)	(2.74)	(-1.43)	(-0.22)	(1.67)	(1.88)	(-0.60)	(-0.57)
Other housing	0.342	0.332	-0.021	0.028	0.138**	0.139**	-0.054	-0.055
	(0.04)	(0.04)	(-0.24)	(0.33)	(2.28)	(2.27)	(-0.97)	(-0.97)
Single	0.019	0.022	-0.066*	-0.053	0.052**	0.052**	0.028	0.032
	(0.53)	(0.61)	(-1.69)	(-1.38)	(2.19)	(2.20)	(0.90)	(0.99)
Separated/Divorced	0.018	0.017	-0.022	-0.004	-0.174**	-0.180**	0.053	0.054*
	(0.41)	(0.38)	(-0.25)	(-0.05)	(-2.09)	(-2.14)	(1.65)	(1.70)

Table 7. Effects in the predicted probabilities in Beijing and Shanghai.

		Car		*PT*		*AT*	
		β×mean	β×Δ1SD	β×mean	β×Δ1SD	β×mean	β×Δ1SD
Beijing	η_{home}	–	–	–	–	+11.0%	+2.2%
	$\eta_{external}$	+3.5%	+5.7%	–	–	−3.2%	−5.4%
Shanghai	η_{home}	–	–	–	–	–	–
	$\eta_{external}$	+18.6%	+5.7%	−12.8%	−3.9%	−5.8%	−1.8%

4. Discussion

This paper analyzed the relationship between pro-environmental behaviour and commuting mode in four Asian megacities: Tokyo, Beijing, Shanghai and Singapore. Overall, the results show varying relationships between environmental preferences and travel mode choice among the studied cities. The results indicate that pro-environmental preferences do not universally increase the likelihood of choosing environmentally friendly travel modes.

The comparative results emphasize the importance of city-based analyses. Despite the robust positive relation between pro-environmental preferences and environmentally friendly travel mode choices in European cities, we do not find a similar significant relationship in Tokyo and Singapore, both of which are among the most developed cities in the world. These results provide supporting evidence of habit discontinuity and self-activation in Beijing and Shanghai, where changes in the transportation infrastructure and in the availability of travel modes are changing rapidly. As suggested by Verplanken et al. (2008), when habits are disrupted by changes in the environment where the behaviour takes place, environmental concerns become relatively more prominent determinants of travel mode choice (Verplanken & Wood, 2006; Wood et al., 2005). Indeed, the share of respondents who had experienced new access to urban infrastructure within six months of the survey date in Beijing and Shanghai was approximately three times higher than that of Tokyo and Singapore (9.5% in Beijing and 10.9% in Shanghai, compared with 3.7% in Tokyo and 2.8% in Singapore).

The results show that (1) commuters who engage in environmentally friendly actions, such as recycling and energy saving, have a higher likelihood of commuting by bicycle/on foot in Beijing, and (2) commuters who participate in environmental activities organized by the government, corporations or other organizations are less likely to use environmentally friendly commuting modes in Beijing and Shanghai. The former result of a positive relationship between environmentally friendly household actions and a pro-environment travel mode choice is consistent with previous findings (Johansson et al, 2006). However, the latter result suggests a possible substitution effect rather than complementarity for participation in organized pro-environment activities and pro-environment travel mode choices. Pro-environmental activities that are embedded in daily home activities could be complementary to environmentally friendly travel mode choices, but other activities that are organized by external organizations seem to act as a substitute in some cases.

The contribution of our study is to shed light on the existence of substitutive effects between eco-friendly actions, which have been ignored due to the assumption that previous studies have made. Most of the previous studies have focused on environmental awareness only towards travel behaviour and not focused on environmental attitudes towards other eco-friendly actions (e.g. Schwanen and Mokhtarian 2005; Gardner and Abraham, 2010; Klöckner and Blöbaum, 2010; Lind et al., 2015). Our results implied that in addition to environmental awareness towards transport, other environmental behaviours have to be recognized as determinants of modal choice towards sustainable transportation.

Our results emphasized the importance of focusing on the difference in the types of environmentally friendly actions, rather than the difference in cities. While daily environmental actions at home show positive relation to environmentally friendly modal choice in both the previous study (Johansson et al, 2006) and this study, we originally found the negative relationship between external environmental activities in Beijing and Shanghai. This implied that there may exist the substitution between costly environmental activities and eco-friendly travel mode choice among commuters also in Western countries, which have been ignored among previous studies focusing on Western cities. Further analysis is needed to investigate the difference in areas and difference in types of activities simultaneously.

Due to the possible existence of the substitution effects, some CSR activities such as afforestation might discourage eco-friendly commuting among employees. One of the effective solution is offering employees an incentive to commute by using environmentally friendly travel modes, which is represented by commuting allowance for using green transportation. Suzuki and Nakamura (2017) focused on commuting allowance for cyclists and, however, found that the reduction in CO2 emission by the commuting allowance was small. Building an effective financial support system for green commuting is still on the way. On the other hand, peak hour avoidance (PHA) is recognized as another way that can address this issue. The aim of PHA is at offering car commuters incentives for not driving during peak hours. Supporting PHA is recognized to improve environmental situation through reducing congestion, which can reduce greenhouse gas emissions (Noordegraaf and Annema, 2012; Kenworthy, 2008).

Although Scope 3 is a broad concept and there are difficulties in calculating all of the amount of Scope 3 emissions precisely, reporting the Scope 3 has been gradually widespread among companies. Moreover, it has been implicated that promoting employees' greener commuting improves environmental quality through reducing Scope 3 emissions (Onat et al., 2014; Stein and Khare, 2009; Matthews et al., 2008). To realize sustainable supply chain management efficiently, we need to be more concerned about reduction in Scope 3 emissions.

This study has several limitations that future studies may address. We found robust differences in the results on pro-environmental activities and commuting modes across the examined cities, but the set of indicators we used to construct the latent variables in the choice model differed from that of previous studies that focused on different cities and regions. If it is possible that the results are sensitive to the set of indicators of environmental perception that we used, then survey data from various cities and regions with a common set of indicators are needed to further check the reliability of the results and to determine whether the relationships between subjective environmental factors and environmental friendly mode choices are systematic.

The sample size of our analytical data is relatively smaller than common empirical studies. Generally, smaller sample size causes lower statistical power, which means that the results are more likely to show no significant difference even if there is difference in reality (Vergouwe et al, 2005; Björklund and Swärdh, 2017). In addition, small sample size in logistic regression may overestimate the effects of explanatory variables. Long et al. (1997) suggested that the sample size smaller than 100 is not enough to maximum likelihood estimation, while sample size larger than 500 seem adequate. Moreover, additional observations per each additional unknown parameter are needed. Nemes et al. (2009) argued that the necessary sample size varies depending on the data structure, so that Long's numerical suggestion may not be all true every time.

Moreover, we used MNL to obtain the marginal effects on the probability of choosing each commuting mode category, which enabled us to interpret the magnitude of the impacts. However, MNL does not consider the similarities between the categories of the dependent variable, whereas other choice models, such as multinomial probit and mixed logistic models, can take such similarities into account. Given that recent methodological advances have facilitated the calculation of marginal probabilistic effects, using the other methods may improve the incisiveness of the results.

Lastly, the recent development of the hybrid choice model, which includes latent variables in the conventional choice model with objective factors, enabled us to consider the impact of subjective determinants and improve the explanatory power of the estimation model. The hybrid choice model requires further improvement to enhance the preciseness of travel demand forecasting. Such an effort could also help policy makers and planners on the ground to analyze and clarify the ways to control travel demand by stimulating people's subjective preferences and improving people's utility by improving transportation systems to meet their preferences.

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Footnotes

1. Research in the field of environmental psychology and behaviour provides theories that relate environmental awareness and pro-environmental behaviour (Bamberg et al., 2007). The norm-activation model (Schwartz, 1977; Nordlundand Garvill, 2002; Klöckner and Matthies, 2004) and the value-belief-norm theory (Stern, 2000; Collins and Chambers, 2005; Lind et al., 2015) assume that pro-environmental behaviour has pro-social and normative motives. In contrast, the theory of planned behaviour argues that self-interest determines behaviour (Ajzen, 1991; Bamberg et al., 2007; Donald et al., 2014). Recent studies have used frameworks that combine the abovementioned theories (Klöckner and Blöbaum, 2010; Van Acker et al. 2010; Schneider, 2013). This leaves to future study that psychological factors play important role and context applies to what extent (Khanal et al., 2018).

2. For more detailed information about our survey, see Chapman et al. (2019).

Appendix

Table A.1. The definition of variables.

Variable	Definition
Recycling/sorting (y_1)	Dummy=1 if the respondent takes recycling or sorting rubbish/reduction of rubbish
Cleaning (y_2)	Dummy=1 if the respondent takes cleaning or gathering rubbish in his/her neighborhood
Energy saving (y_3)	Dummy=1 if the respondent takes energy saving actions
Recycled goods (y_4)	Dummy=1 if the respondent takes purchasing recycled goods
Energy-saving goods (y_5)	Dummy=1 if the respondent takes purchasing of energy saving household products
Government (y_6)	Dummy=1 if the respondent participates environmental action organized by government
Corporations (y_7)	Dummy=1 if the respondent participates environmental action organized by corporations
International (y_8)	Dummy=1 if the respondent participates environmental action organized by international organizations
Education (y_9)	Dummy=1 if the respondent participates environmental education
Animal protection (y_{10})	Dummy=1 if the respondent participates animal protection
Forest protection (y_{11})	Dummy=1 if the respondent participates protection of forest
Policy (y_{12})	Dummy=1 if the respondent participates activities related to environmental policy
Meetings (y_{13})	Dummy=1 if the respondent participates meetings or demonstration on environment issues
Female	Dummy=1 if the respondent is female
Age	respondent's age
ln(Income)	Natural log of income
Education	Years of education
Child	The number of children the respondent has
Apartment (rent)	Dummy=1 if the respondent lives in Apartment/mansion (renting)
Apartment (own)	Dummy=1 if the respondent lives in Apartment/mansion (own)
House (rent)	Dummy=1 if the respondent lives in single family home (renting)
House (own)	Dummy=1 if the respondent lives in single family home (own)
Other housing	Dummy=1 if the respondent lives in other residential types
Single	Dummy=1 if the respondent is single
Separated/Divorced	Dummy=1 if the respondent is separated/divorced
Type of industry	Dummy variables of sixteen types of industry
Personality	Three variables constructed by factor analysis of ten indicators of personality (Gosling et al., 2003)
Regional dummies	Dummy variables of regions in each city

Table A.2. Summary statistics of explanatory variables.

	Tokyo		Beijing		Shanghai		Singapore	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
η_{home}	0.693	0.176	0.711	0.144	0.932	0.225	0.435	0.158
η_{external}	0.165	0.101	0.0815	0.135	0.554	0.169	0.155	0.162
Female	0.368	0.483	0.435	0.496	0.569	0.495	0.492	0.501
Age	46.27	11.88	41.41	10.50	41.88	10.14	42.83	11.58
ln (Income)	11.10	0.634	9.872	0.721	10.03	0.683	10.89	0.703
Education (years)	15.56	1.729	15.47	1.701	15.16	2.387	14.79	2.555
Child	0.882	1.035	0.998	0.546	0.931	0.520	1.053	1.132
Apartment (own)	0.307	0.461	0.780	0.415	0.857	0.350	0.619	0.486
House (rent)	0.0184	0.135	0.0290	0.168	0.0166	0.128	0.0279	0.165
House (own)	0.279	0.449	0.104	0.305	0.0762	0.265	0.231	0.422
Other housing	0.0158	0.125	0.0127	0.112	0.00614	0.0782	0.0685	0.253
Single	0.317	0.466	0.0906	0.287	0.112	0.315	0.350	0.478
Separated/Divorced	0.0697	0.255	0.00845	0.0916	0.0160	0.125	0.0533	0.225
Observations	760		1,656		1,628		394	

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