Chapter 8

Influence of pricing on mode choice decision integrated with latent variable: the case of Jakarta Greater Area

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Chapter outline

1. Introduction

Jakarta Government had implemented a 3 in 1 high-occupancy vehicle (HOV) policy on several arterial roads in Jakarta CBD (Governor of DKI Jakarta Province, 2012) between 1994 and 2016 (Sidiq, 2018), here private cars with less than three persons are not allowed to travel on arterial roads during morning and evening peak hours. Unfortunately, this policy has not been successful in improving urban transport conditions due to lack of control and some further implementation issues. There are people that willing to be paid to fulfill the minimum number of passengers on the street (Anya and Wardhani, 2016). This led to the revocation of this policy (Governor-of-Jakarta-Regulation, 2003). Due to the fraud of 3 in 1 policy, there is a movement to replace it with a more comprehensive approach such as Electronic Road Pricing (ERP), which can minimize the fraud and

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increase the accountability. Jakarta Government also had implemented motor cycle restrictions on several roads since 2014 but this policy was stopped in 2017 (Hutabarat, 2017). Moreover, it followed up by implementing an even-odd license plate policy in 2016, as the government is not yet ready to implement Electronic Road Pricing (ERP) (Sidiq, 2018).

ERP has been successfully implemented in several countries. For example, Singapore has succeeded to shift private car users to use public transport by 10%−20% (Agarwal and Koo, 2016). The ALS (Area Licensing Scheme) in London has significantly reduced the private vehicle miles (Santos, 2005). Other examples include Milan (Rotaris et al., 2010) and Stockholm (Eliasson and Mattsson, 2006). Several studies have been conducted on the feasibility of ERP in Jakarta. Prayudyanto et al. (2013) evaluated several approaches to the implementation of congestion charging. Sugiarto et al. (2015, 2016) have explored the psychological factors that influence the public acceptance of ERP schemes. Their results emphasize that a clear introduction and explanation of the benefits of the ERP policy might increase public acceptance of its implementation.

This research is employing a SP (stated preference) survey to explore respondents' mode choice preferences when there are pricing scheme such as road pricing, parking cost and transport cost changes in Jakarta. There are several studies that have implemented SP to measure the impact of pricing (see, for example, (Milioti et al., 2008) in Athens; (Vrtic et al., 2009) in Switzerland; (Yagi and Shiraishi, 2017) in Abidjan). They found that pricing schemes reduce the market shares of the priced means of transport.

As the earlier studies, this paper evaluates potential pricing schemes (road pricing, parking cost, and transport cost), but does so simultaneously. Other contribution of this paper is to employ latent variables (LVs) in mixed logit (MXL) and Multinomial Logit (MNL) to capture attitude and perceptions of person. It is the first such study for Jakarta. Given the importance of clearly explaining the benefit of ERP the respondents are told prior to the survey that the ERP will contribute for improving public transport, building new infrastructure, financing transport services, etc. Since the emphasis is on the "contribution," in this study the term ERP or road pricing is replaced by "contribution cost," in order to avoid any negative perception during the survey and present the positive message that the respondents will contribute to improving the present public transport system.

In this paper, not only the model estimates are presented but also value of time (VoT) and elasticities for the sample. We use multinomial logit model (MNL) and the mixed logit model (MXL) for the parameter estimation, which incorporates factor scores to capture attitudes using Latent Variables (LVs) for our analysis.

The remainder of this paper is structured as follows. In Section 2, we explain about data and its methods collection. In Section 3, we explain descriptive analysis of the data. In Section 4, we describe application of apply

MNL and MXL for model estimation. In Section 5, the results of the influence of road pricing are described, including the value of travel time savings. Conclusions are discussed in Section 6.

2. Data and methods

2.1 Survey design

The survey is designed to measure mode choice preferences in the Greater Jakarta Area. The survey consists three parts: Stated Preference (SP), socio demographic, and attitudinal questions. This survey is focused on the impact of pricing schemes such as changed travel costs, parking costs, and especially road pricing/congestion charging in Jakarta. Therefore, the attitudinal questions try to identify attitude/perceptions of respondents toward congestion charging.

The first part is the Stated Preferences (SP) survey. There are four means of transportation; public transport (PT), park and ride, car, and motorcycle. The respondents were told that public transport refers to all regular public transport services such as TransJakarta (Jakarta Bus Rapid Transit), commuter rail, regular bus, and mini-bus. Park and ride was defined as driving a private vehicle to a PT terminal or station and park their vehicle there before continuing the trip using PT. Park and ride is included, as the number of people who commute is around 3.6 million people, which equal to 12.7% of the total population (BPS-Statistics, 2014). In the SP experiment, the attributes are travel time, travel cost, waiting time, transfers, congestion charging (here it is called contribution cost) and parking costs. The variable travel cost is related to the fuel costs for motor cycle and car, ticket fares for public transport, and combines both fuel costs and fares for park and ride.

The experimental designs for SP were developed by Ngene with a D-efficient design (Rose and Bliemer, 2004). There are 36 choice experiments divided into three blocks, of which each respondent receives one. The possible values of each variable is presented in Table 8.1. The costs (Travel, parking, and contribution cost) are displayed in thousands (1K) IDR, which around 0.07 US$ at 25th June 2018.

The second part of the questionnaire asked for the respondent's socio-demographic characteristics such as age, gender, and income. The third part of the questionnaire asked about attitudinal questions regarding their perception of congestion charging using a Likert scale from 1 to 5 as shown below:

1. Improvement in public transport is significant to me
2. The number of private vehicles should be reduced
3. It is reasonable for public transport services cost to be partially funded by a contribution cost paid by private vehicle users
4. It is reasonable for public transport infrastructure to be partially funded by a contribution cost paid by private vehicle users
5. Traffic congestion is a significant problem in Jakarta

TABLE 8.1 Attributes and their values in SP experiments.

Attribute	Public transport	Park and ride	Car	Motorcycle
Travel time (minute)	30, 45, 60, 75	30, 45, 60, 75	30, 45, 60, 75	20, 30, 40, 60
Travel cost (IDR 1k)	4, 8, 12, 16, 20	8, 12, 16, 20, 25	12, 16, 18, 20, 25	4, 8, 12, 16
Waiting time (minute)	10, 15, 20, 25	10, 15, 20, 25	0	0
Transfer	0, 1, 2, 3	1, 2, 3	0	0
Contribution cost (IDR 1k)	0	0	10, 15, 20, 25	5, 8, 10, 12
Parking cost (IDR 1k)	0	4, 6	5, 10	2, 4, 6

2.2 Pre-test

Before the main survey, we sent a pre-test survey to 40 respondents to identify possible problems and limitations and adjusted the questionnaire as required. There were several problems that we found during pre-test survey:

- The respondents could not save the survey form because of the format of birth of date
- Some respondents were asking about the meaning of park and ride, though we had explained it in the instructions
- The respondents were confused whether they should provide monthly or yearly incomes

Based on those finding, we correct the survey format and start the final survey, as explained in Section 2.3.

2.3 Data collection

The data were collected using ETH Zurich online survey tools (www.selectsurvey.ethz.ch). The survey link was distributed in several social media groups (Facebook, Instagram, Twitter, and WhatsApp) and also to some colleagues asking their help to distribute the questionnaire. The respondents of our survey are people who live in Jakarta or the Greater Jakarta Area (Bogor, Depok, Tangerang, and Bekasi) and must have activities in Jakarta. We assume that the respondents have access to all means of transport.

At first, we obtained 262 online respondents. Then we expand the survey by asking a survey company to find respondents and help them fill out the questionnaire. After some data cleaning, 496 respondents in total completed the questionnaire in full, with a total of 5879 choice observations. Based on the results of choice SP survey, there are 40.98% of respondents choose motor cycle, 26.99% of respondents choose public transport, 17.69% of respondents choose car, and 14.34% of respondents choose park and ride.

3. Descriptive analysis

3.1 Socio-demographics

The sample socio-demographics are presented Table 8.2. 54.20% of respondents are male with most of the respondents having an income of more than IDR 10 million per month (approximately 700 US$ or 1878 US$ at purchasing power parity). In addition, 42.81% of respondents commute between 10 km and 25 km. There are differences between the sample and the population in Greater Jakarta Area. For gender, the difference is not large. However, the age of the respondent distribution does not match the population distribution, for example respondents between 24−29, and 29−34 years are over-represented. Moreover, for income and commuting distance, we do not have matching census information.

We do a factor analysis to identify Latent Variables (LVs) based on the attitudinal questions with Likert scale (strongly disagree to strongly agree), which has been used for measuring attitude and can express how much a person agree with a statement (Likert et al., 1993). We applied minimum residual approach to select these factors using Varimax rotation, and we found that Root Mean Square Error of Approximation (RMSEA) index is 0.022, which shows good model fit as it is below 0.050. Furthermore, the value of Cronbach's α (= 0.932; measures the reliability of the latent constructs) and the Kaiser-Meyer-Olkin (KMO) criterion (= 0.81; measures the degree of sampling adequacy) are considered acceptable. We found that there are two LVs; pro funding of public transport (FUND_PT), and contra private car (ANTI_CAR). The questions L1, L2, and L5 belong to LV1 (FUND_PT), and L3 and L4 are belong to LV2 (ANTI_CAR) (see Table 8.3 and Fig. 8.1).

To understand possible correlations between socio-demographics of respondents with the factor scores of the attitudinal question we calculate all correlation coefficients. Socio-demographic variable included are:

- Male (dummy)
- Age (continuous)
- Personal income (continuous; mean normalized)
- Living with family (dummy)

TABLE 8.2 Respondent characteristics.

Variable	Value	Sample (%)	Census (%)
Gender	Male	54.20	50.58
	Female	45.80	49.42
Age (years)	Less than 24	44.75	44.09
	24–29	28.71	9.19
	29–34	11.35	9.10
	34–39	5.78	8.44
	39–44	3.20	7.39
	44–49	2.43	6.22
	49–54	1.82	5.01
	More than 54	1.96	10.54
Income (in IDR per month)	Less than IDR 1000 K	1.39	NA
	IDR 1000 K–2000 K	5.89	NA
	IDR 2000 K–6000 K	27.00	NA
	IDR 6000 K–10,000 K	19.64	NA
	More than IDR 10,000 K	46.08	NA
Commuting distance (km)	No answer	1.60	NA
	Less than 5	28.75	NA
	5–10	14.93	NA
	10–25	42.81	NA
	More than 25	11.90	NA

Fig. 8.1 shows the overview on how attitudes are linked to socio-demographics attributes. It shows that both attitudes ANTI_CAR and FUND_PT are higher for men in lower age groups and income.

4. Modeling approach

In this paper, we employ two different models using multinomial logit (MNL), introduced by (D. McFadden, 1974) and improved by (Ben-Akiva and Lerman, 1985) and mixed logit model (MXL) or also called random-parameter logit, which was developed by (K. McFadden and Train, 2000). The problems of attitude and perceptions of person are addressed using latent variables (LVs)

TABLE 8.3 The factor weights.

Factor	Attitudinal questions	FUND_PT	ANTI_CAR
L1	Improvement in public transport is significant to me	0.90	0.39
L2	The number of private vehicles should be reduced	0.81	0.42
L3	Support for funding public transport services	0.37	0.85
L4	Support for funding public transport infrastructures	0.32	0.83
L5	Traffic congestion is a significant problem	0.91	0.38

and included in the utility formulation. We apply two LVs based on the result of factor analysis; LV1 (s = 1) is pro funding public transport and LV2 (s = 2) is contra with private car, which can be seen in Fig. 8.2.

The parameters for cost (c), such as travel cost $(\beta_{travelCost})$, parking costs $(\beta_{parkingCost})$ contribution cost $(\beta_{contributionCost})$, are generic, but with continuous interaction terms with income according to (Mackie et al., 2003). The *income* is the individual gross income, *meanIncome* is sample mean of income, and corresponding elasticity the variable of income λ_{income}. The formulation is as follows in Eq. (8.1):

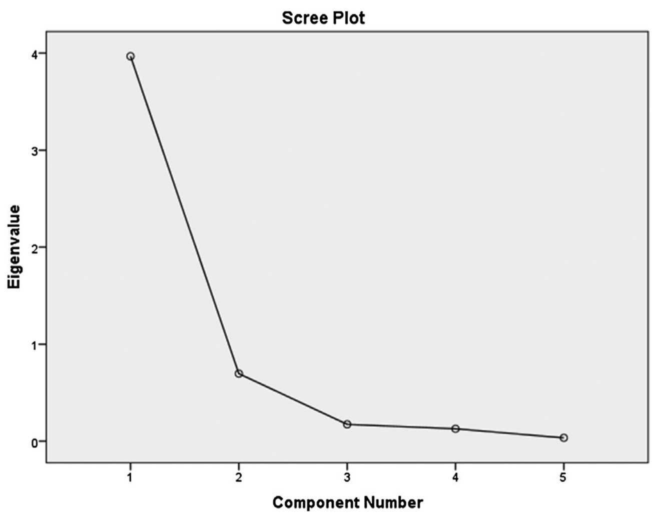

FIG. 8.1 Scree plot of factor number.

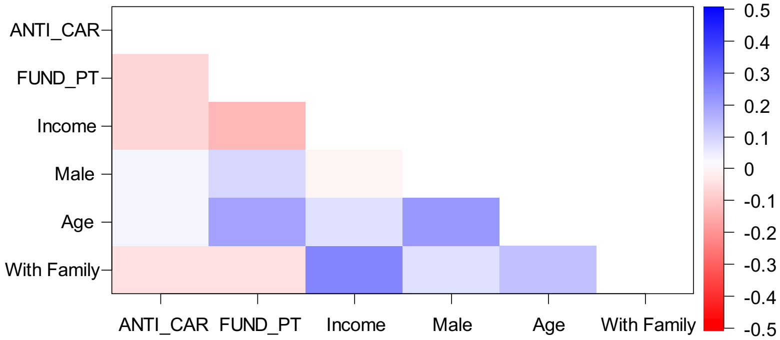

FIG. 8.2 Correlation of socio-demographic and attributes.

$$f_c = \beta_C \left(\frac{Income}{meanIncome} \right)^{\lambda_{inCome}} Costs_c \tag{8.1}$$

The utility if person n choosing alternative i in choice situation t is given by, for MNL and for MXL. The details of utility in MNL and MXL which include LVs are given in Tables 8.4 and 8.5. There are four utility functions with four alternatives specific constant (ASC), such as public transport ($i = 1$), park and ride ($i = 2$), car ($i = 3$), and motorcycle ($i = 4$). However, public transport ($i = 1$) is base category, and we do not include the LVs for base category. The formulation is summarized below:

$$U_{i,n,t} = ASC_i + X_{i,n,t}\beta_{i,n,t} + f_{c,n} + \varepsilon_{i,n,t} \tag{8.2}$$

$$U_{i,n,t} = ASC_i + X_{i,n,t}\beta_{i,n,t} + f_{c,n} + X_{i,n,t}LV_{s,i,n,t} + \varepsilon_{i,n,t} \tag{8.3}$$

$$U_{i,n,t} = \left(ASC_i + \eta_{i,n}\right) + X_{i,n,t}\beta_{i,n,t} + f_{c,n} + \varepsilon_{i,n,t} \tag{8.4}$$

$$U_{i,n,t} = \left(ASC_i + \eta_{i,n}\right) + X_{i,n,t}\beta_{i,n,t} + f_{c,n} + X_{i,n,t}LV_{s,i,n,t} + \varepsilon_{i,n,t} \tag{8.5}$$

The error $\varepsilon_{i,n,t}$ is assumed to be distributed IID extreme value. The formula Eq. (8.2) describes for MNL model (M1), the formula Eq. (8.3) for MNL with LVs (M2), formula Eq. (8.4) for MXL (M3), and formula Eq. (8.5) for MXL with LVs (M4). However, the random coefficient for MXL are used in ASCs, which decomposed into their mean value of ASC and by deviation denoted $\eta_{i,n}$. We obtain significant values for all ASC for MXL model. Furthermore, the full formulation utility function of the model using LVs are described in Table 8.4 for MNL, and for MXL model are described in Table 8.5.

To measure the value of time (VoT), i.e. how much money (e.g. Indonesian Rupiah - IDR) a person is willing to pay for a reduction of travel time unit (e.g. hour), we can use the formula in Eq. (8.6) to calculate it. Where V_{in} represents systematic utility for an alternative i for person n, T_{in} represents travel time for the person n choosing an alternative i, and C_{in} represent the cost for the person

TABLE 8.4 Utility function of mode choice (MNL model).

$$U_{publicTransport} = \beta_{travelTimePT} * travelTime + \beta_{travelCost} * \left(\frac{income}{meanIncome}\right)^{\lambda_{income}} * travelCost + \beta_{transferPT} * transfers + \beta_{waitingTime} * waitingTime$$

$$\begin{aligned} U_{parkandRide} = {} & ASC_{PR} + \beta_{travelTimePR} * travelTime \\ & + \beta_{travelCost} * \left(\frac{income}{meanIncome}\right)^{\lambda_{income}} * travelCost \\ & + \beta_{transferPR} * transfer + \beta_{waitingTimePR} * waitingTime \\ & + \beta_{parkingCost} * \left(\frac{income}{meanIncome}\right)^{\lambda_{income}} * parkingCosts \\ & + \beta\_FUND\_PT\_PR * (fund\_pt) \\ & + \beta\_ANTI\_CAR\_PR * (anti\_car) \end{aligned}$$

$$\begin{aligned} U_{car} = {} & ASC_{Car} + \beta_{travelTimeCar} * travelTime \\ & + \beta_{travelCost} * \left(\frac{income}{meanIncome}\right)^{income} * travelCost \\ & + \beta_{contributionCost} * \left(\frac{income}{meanIncome}\right)^{\lambda_{income}} * ContributionCost \\ & + \beta_{parkingCost} * \left(\frac{income}{meanIncome}\right)^{\lambda_{income}} * parkingCost \\ & + \beta\_FUND\_PT\_C * (fund\_pt) * \beta\_ANTI\_CAR\_C * (anti\_car) \end{aligned}$$

$$\begin{aligned} U_{motorcycle} = {} & ASC_{MC} + \beta_{travelTimeMC} * travelTime \\ & + \beta_{travelCost} * \left(\frac{income}{meanIncome}\right)^{\lambda_{income}} * travelCost \\ & + \beta_{contributionCost} * \left(\frac{income}{meanIncome}\right)^{\lambda_{income}} * ContributionCost \\ & + \beta_{parkingCost} * \left(\frac{income}{meanIncome}\right)^{\lambda_{income}} * parkingCost \\ & + \beta\_FUND\_PT\_MC * (fund\_pt) \\ & + \beta\_ANTI\_CAR\_MC * (anti\_car) \end{aligned}$$

TABLE 8.5 Utility function of mode choice (MXL model).

$$U_{publicTransport} = \beta_{travelTimePT} * travelTime + \beta_{travelCost} * \left(\frac{income}{meanIncome}\right)^{income} * travelCost$$

$$+ \beta_{transferPT} * transfers + \beta_{waitingTime} * waitingTime$$

$$U_{parkandRide} = ASC_{PR\_RND} + \beta_{travelTimePR} * travelTime$$

$$+ \beta_{travelCost} * \left(\frac{income}{meanIncome}\right)^{income} * travelCost$$

$$+ B\beta_{transferPR} * transfer + \beta_{waitingTimePR} * waitingTime$$

$$+ \beta_{parkingCost} * \left(\frac{income}{meanIncome}\right)^{\lambda_{income}} * parkingCosts$$

$$+ \beta\_FUND\_PT\_PR * (fund\_pt)$$

$$+ \beta\_ANTI\_CAR\_PR * (anti\_car)$$

$$U_{car} = ASC_{Car\_RND} + \beta_{travelTimeCar} * travelTime$$

$$+ B\beta_{travelCost} * \left(\frac{income}{meanIncome}\right)^{income} * travelCost$$

$$+ \beta_{contributionCost} * \left(\frac{income}{meanIncome}\right)^{income} * ContributionCost$$

$$+ \beta_{parkingCost} * \left(\frac{income}{meanIncome}\right)^{income} * parkingCost$$

$$+ \beta\_FUND\_PT\_C * (fund\_pt)$$

$$+ \beta\_ANTI\_CAR\_C * (anti\_car)$$

$$U_{motorcycle} = ASC_{MC\_RND} + \beta_{travelTimeMC} * travelTime$$

$$+ \beta_{travelCost} * \left(\frac{income}{meanIncome}\right)^{income} * travelCost$$

$$+ \beta_{contributionCost} * \left(\frac{income}{meanIncome}\right)^{\lambda_{income}} * ContributionCost$$

$$+ \beta_{parkingCost} * \left(\frac{income}{meanIncome}\right)^{\lambda_{income}} * parkingCost$$

$$+ \beta\_FUND\_PT\_MC * (fund\_pt)$$

$$+ \beta\_ANTI\_CAR\_MC * (anti\_car)$$

n choosing an alternative n. The parameters of time and cost are represented by β_T and β_C respectively.

$$VoT_{i,n} = 60x\frac{\partial V_{i,n}/\partial T_{i,n}}{\partial V_{i,n}/\partial C_{i,n}} = 60x\frac{\beta_T}{\beta_C} \tag{8.6}$$

5. Results and discussion

5.1 Model estimation

We present four different modes as described in Section 4; MNL (M1), MXL (M2), MNL incorporating latent variables (M3), and MXL incorporating latent variables (M4). We use 500 Halton draws for the estimation of MXL models (Table 8.6). Generally speaking, based on the values of final-LL, AIC, Rho-square, and BIC, we found that M4 outperforms the other models, and the models with latent variables (M3 and M4) outperform the models without them (M1 and M2). Moreover, MXL model (M2 and M4) outperform MNL model (M1 and M3). Below we discuss the results from M3 and M4.

Table 8.6 also presents the alternative specific constants (ASCs) for each mode. For identification the public transport ASC is set to zero as a base category. In model M3 ASC car is not significance but in model M4 ASC car is negative and significant. The ASC motorcycle negative and significant in both models. The negative ASCs indicate that the relevant mode preferred over the base category/public transport.

The latent variables Anti-car (L1) and Pro-funding PT (L2) have no significant impact on park and ride in both models. However, the impact of L1 is positive and significant and L2 is negative and significant for motorcycle in model M3 but not significant in model M4. Moreover, the impact of L2 is negative and significant for car in both models, and negative but at a lower level of significance for L1 in both models.

Overall, L1 and L2 have a significant influence on mode choice. Model M3 shows this impact for all modes, while model M4 shows it only for car. We find it interesting that L1 is positive and significant for motor cycle while it is negative for the other modes. This might be due to respondents who agree with L1 tend to choose motor cycle as means of transport, and this correlates with traffic congestion in Jakarta where motor cycle are faster. In addition, online motor cycle ride sharing is rapidly increasing in Jakarta (for example: Gojek, Grab, and Uber).

Moreover, transfers, waiting time for public transport and park and ride has a negative and significant influence in both models. In other words, reducing the number of transfers can be alternative to speed increases but for park and ride it will have less impact based on our results.

In addition, if we look at pricing such as Travel Cost, Parking Cost and Congestion Charging. We found that those variables are negative and significant for all means of transport affected in both models. Pricing will be effective in Transport Demand Management (TDM) when one wants to reduce private vehicle use.

TABLE 8.6 Model estimation.

Mode	Variables	MNL (M1)		MXL (M2)		MNL latent (M2)		MXL latent (M4)	
		Estimation	*t*-test	Estimation	*t*-test	Estimation	*t*-test	Estimation	*t*-test
Base category: Public transport	*Model estimation*								
	Travel cost	−0.0143	−3.99	−0.0422	−5.42	−0.0155	−4.06	−0.0434	−5.81
	Lambda cost	−0.4018	−9.38	−0.2588	−4.44	−0.3945	−8.97	−0.253	−4.44
	Congestion charging	−0.0349	−6.46	−0.0295	−3.32	−0.0328	−6.03	−0.0283	−3.25
	Parking cost	−0.037	−4.72	−0.0464	−3.43	−0.0369	−4.70	−0.0454	−3.33
Public transport	Travel time	−0.0475	−21.86	−0.0782	−24.00	−0.0475	−21.78	−0.0782	−24.04
	Transfer	−0.2113	−5.66	−0.268	−4.77	−0.2019	−5.36	−0.2608	−4.71
	Waiting time	−0.0155	−2.67	−0.0246	−3.12	−0.0158	−2.72	−0.0245	−3.11
Park and ride	ASC/ RND_ASC	−0.5685	−1.91**	−1.2205	−2.96	−0.5552	−1.86**	−1.2485	−3.03
	Travel time	−0.0425	−15.67	−0.0658	−17.47	−0.0427	−15.70	−0.0659	−17.51
	Transfer	−0.1602	−2.91	−0.0724	−0.92*	−0.1541	−2.75	−0.0678	−0.87*
	Waiting time	−0.0243	−3.29	−0.0508	−5.12	−0.0242	−3.27	−0.0503	−5.05
	Anti-car	–	–	–	–	−0.0731	−1.47*	−0.066	−0.63*
	Pro-funding-PT	–	–	–	–	−0.3089	0.84*	−0.012	−0.10*
	Sigma ASC	–	–	–	–	–	–	2.1449	17.00

Car	ASC/ RND_ASC	−0.3212	−1.33**	−1.4018	−3.70	−0.3297	−1.360*	−1.4297	−3.76
	Travel time	−0.0418	−16.31	−0.0746	−18.73	−0.0426	−16.47	−0.074	−18.60
	Anti-car	–	–	–	–	−0.0731	−1.85**	−0.2614	−1.66**
	Pro-funding-PT	–	–	–	–	−0.3089	−7.31	−0.7137	−4.84
	Sigma ASC	–	–	–	–	–	–	2.9846	15.03
Motor cycle	ASC/ RND_ASC	−1.0918	−5.34	−1.8814	−5.61	−1.0817	−5.26	−1.8938	−5.76
	Travel time	−0.0439	−21.83	−0.0887	−25.76	−0.0442	−21.88	−0.0891	−25.76
	Anti-car	–	–	–	–	0.068	2.11	0.156	1.22*
	Pro-funding-PT	–	–	–	–	−0.1365	−4.02	−0.1955	−1.33*
	Sigma ASC	–	–	–	–	–	–	3.227	17.08

Continued

TABLE 8.6 Model estimation.—cont'd

Mode	Variables	MNL (M1)		MXL (M2)		MNL latent (M2)		MXL latent (M4)	
		Estimation	*t*-test	Estimation	*t*-test	Estimation	*t*-test	Estimation	*t*-test
	Model fit								
	Observations	5879							
	Draws			500				500	
	Final-LL	−6708.85		−4837.74		−6661.66		−4824.28	
	Rho-square	0.177		0.406		0.183		0.408	
	AIC	13447.71		9711.47		13365.31		9696.57	
	BIC	13547.89		9712.91		13505.57		9856.87	

*Not significant; **significant at 10% level.

5.2 Value of time

Table 8.7 provides the relative ratios of variables at the sample means between costs and time (Value of time (VoT)) for both models including the latent variables. We found interesting results comparing these two models. For MNL Model, the VoT for congestion charging is higher than the VoT for parking cost but it lower than VoT for fuel/ticket cost, which is similar as be found in (Vrtic et al., 2009). However, in MXL model, we found that the VoT for congestion charging is the highest and followed by fuel/ticket cost, and parking cost. The argument for the difference is the ease by which the travelers can avoid the different costs.

TABLE 8.7 Value of time of variables.

Model	VoT	Public transport	Park and ride	Car	Motor cycle
MNL with latent (M3)	Fuel cost/ticket (IDR/h)	183,871	165,290	164,903	171,097
	Congestion charging (IDR/h)	–		77,927	80,854
	Parking cost (IDR/h)	–	69,431	69,268	71,870
	Waiting time (IDR/h)	61,161	93,677	–	–
	Transfers (IDR/transfer)	13,026	9942	–	–
	Transfers (min/transfer)	4.25	3.61	–	–
MXL with latent (M4)	Fuel cost/ticket (IDR/h)	108,111	91,106	102,304	123,180
	Congestion charging (IDR/h)			156,890	188,905
	Parking cost (IDR/h)		87,093	97,797	117,753
	Waiting time (IDR/h)	33,871	69,539	–	–
	Transfers (IDR/transfer)	6009	1562	–	–
	Transfers (min/transfer)	3.34	1.03	–	–

The mean value of VoT for fuel/ticket cost in public transport is the highest followed by motor cycle, park and ride, and car for MNL model. However, in MXL model VoT of fuel/ticket cost motor cycle is the highest followed by public transport, car, and park and ride. In both models, we found that public transport or motor cycle placed in position one or two in terms of the highest VoT. It shows that respondents react more for car and park and ride because the price of that transport mode is already more expensive than public transport and motor cycle.

Moreover, for VoT of congestion charging and parking cost, both models give same result that motor cyclists are more sensitive than car users. It can be argued that motor cycle use gives more benefits than car use, so that the respondents tend to be more willing to pay more for motor cycle use because it is faster and cheaper, especially in congested Jakarta. The VoT for transfer during park and ride is lower than for public transport only, because park and ride users have already accepted the initial transfer from car to public transport.

Furthermore, since the parameters of the pricing/cost attributes (fuel/ticket cost, congestion charging, and parking cost) have been interacted to be elastic with respect to income (see Tables 8.6 and 8.7). Fig. 8.3 shows the VoT of pricing increasing as a function, which holds for both models.

In addition, based on the 2018 provincial minimum wage (Normala, 2017), the minimum hourly wage for Jakarta is calculated. It is approximately IDR 21,000. It shows that VoT of fuel cost/ticket, congestion charging, parking cost, and waiting time in both model are higher than provincial minimum wage. The average hourly wage for 496 samples, which is approximately IDR 70,000. The VoT of fuel cost/ticket, and congestion charging is higher than the average hourly wage of samples in both model. However, the VoT of parking cost is higher than the average hourly wage of samples for model M4 but it is slightly lower for model M3. The VoT of waiting time is mostly lower than average hourly wage of samples but not for

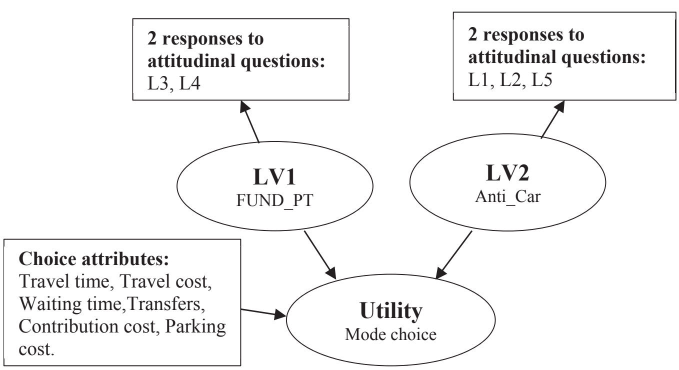

FIG. 8.3 Choice modeling with latent variable.

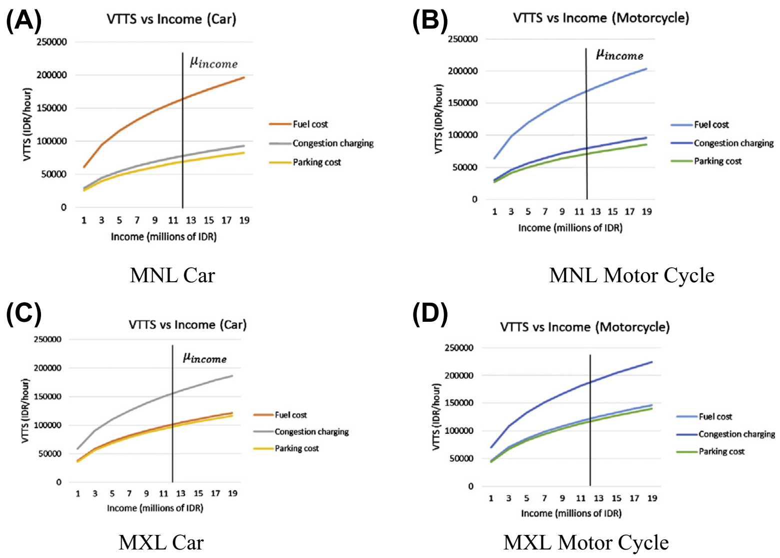

FIG. 8.4 Value of time.

parking cost. While the VoT of transfers are lower than two categories of wage for both models (Fig. 8.4).

6. Conclusion

This study is using an SP survey to investigate factors/variables that influence respondents in their choice of transport mode, compares the result of different models (e.g. MNL and MXL) with and without latent variables, and identify the impact of pricing on mode choice. We found that the models (MNL and MXL) give different results vis-à-vis the significance of different variables, but the signs are consistent with expectations. Overall the estimated models show realistic results.

Jakarta faces acute traffic congestion and people rely on the private car. To find the strength of the variables influencing mode choice is important for any policy in Jakarta.

In general, the MXL with latent variable model outperforms than other models, and MXL itself are better than MNL models. We found that pricing variables (fuel/ticket cost congestion charging, parking cost) reduce car use. That means those variables can be used for an alternative policy to reduce traffic congestion.

However, the respondents have higher VoTs for congestion charging than for parking costs. That means respondents less sensitive when the parking cost increases than for congestion charging. Furthermore, each mode of transport reacts different in terms of VoT. The VoT of congestion charging and parking pricing are higher for car than for motorcycle. Furthermore, all of VoT value is higher than the minimum hourly wage of Jakarta in both model but not all VoT values is higher than average hourly wage of samples.

For further research should investigate the impact of the socio-demographic characteristics, include a congestion charging and parking pricing scenario, estimate it for different home and work location, explore other latent variables with extensive sets of indicators, and look at online ride sharing transport.

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