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The Commuting Mode Choice of Students of Institut Teknologi Bandung, Indonesia

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Abstract. *This research explored the commuting mode preferences of students living near Institut Teknologi Bandung when a new mode of transportation (i.e., carpool) is introduced to the selection list. Six alternative modes were presented: minibus, car, motorcycle, car-based ride-sourcing, motorcycle-based ride-sourcing, and carpool. The data collection process was conducted using a questionnaire-based stated-preferences survey. It included eight sets of labeled scenarios with a number of attributes: travel time, travel cost, waiting time, transfer amount, access and egress time, frequency, congestion time, baggage cost, and parking cost. A total of 1416 observations were acquired for further analysis. A mixed logit (MXL) model with random cost parameter and random error components was used. From the MXL results, we found that travel cost had no significant influence on the selection of commuting mode among students. This result was unforeseen given the characteristics of Indonesian consumers, who are notoriously sensitive to price. However, based on the results for several significant attributes of carpool as well as from the value of travel time savings and demand calculation, we suggest that carpooling is a valid alternative transport mode for campus commuting. As a pioneer study on student commuting mode selection, this study provided valid and dependable evidence on how students around ITB main campus choose their transportation methods.*

Keywords. *carpool, ITB students, mixed logit, elasticities, value of time.*

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Abstrak. *Penelitian ini mengeksplorasi preferensi moda perjalanan pulang pergi mahasiswa yang tinggal di dekat Institut Teknologi Bandung ketika moda transportasi baru (yaitu angkutan bersama) menjadi salah satu pilihan moda. Terdata enam moda alternatif yang disajikan: angkot, mobil, sepeda motor, taksi daring, ojek daring, dan angkutan bersama. Proses pengumpulan data dilakukan dengan menggunakan metoda survei stated-preference berbasis kuesioner. Survei tersebut meliputi delapan skenario berlabel dengan sejumlah atribut: waktu perjalanan, biaya perjalanan, waktu tunggu, banyaknya perpindahan moda, waktu perjalanan menuju tempat angkutan umum dan waktu perjalanan menuju tempat tujuan, frekuensi kedatangan, waktu kemacetan, biaya bagasi, dan biaya parkir. Sebanyak 1416 pengamatan diperoleh untuk analisis lebih lanjut. Model mixed logit (MXL) dengan parameter biaya acak dan komponen error acak digunakan. Dari hasil MXL, kami menemukan bahwa biaya*

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perjalanan tidak berpengaruh signifikan terhadap pemilihan moda perjalanan pulang pergi di kalangan mahasiswa. Hasil ini tidak terduga mengingat karakteristik konsumen Indonesia yang terkenal sensitif terhadap harga. Namun, berdasarkan hasil untuk beberapa atribut signifikan dari angkutan bersama serta dari nilai penghematan waktu perjalanan dan perhitungan permintaan, kami menyarankan bahwa angkutan bersama adalah moda transportasi alternatif yang valid untuk komuter kampus. Sebagai studi perintis dalam pemilihan moda perjalanan pulang pergi mahasiswa, studi ini memberikan bukti yang valid dan dapat diandalkan tentang bagaimana mahasiswa di sekitar kampus utama ITB memilih metode transportasi mereka.

Keywords. *angkutan bersama, mahasiswa ITB, mixed logit, elastisitas, nilai waktu.*

Introduction

Bandung Metropolitan Area, with a population of 2.5 million people, is currently the third most populated city in Indonesia (Bandung, 2017). With a population density of around 15 thousand per km^2, the traffic conditions in the city are inevitably affected, further exacerbated by the city's weak public transport networks and services, which encourages travelers to use motorcycles to reduce travel cost and time (Dharmowijoyo, Susilo & Karlström, 2018). This is supported by Tarigan *et al.* (2016), who states that paratransit and private vehicles are the primary modes of public transport (PT) due to the lack of mass transport modes. The Bandung City government is currently planning to provide light rail transit (LRT) as an alternative transport mode to solve the traffic congestion problem (Ramdani, 2018). However, there are also other transport modes for Bandung citizens besides minibuses and private vehicles, for example 'online transportation' (e.g., Gojek and Grab).

The existence of online transportation influences travel behavior. In the literature on transportation, besides 'online transportation' several other interchangeable terms are used, such as 'ride sourcing' (Rayle, Dai, Chan, Cervero & Shaheen, 2016; Zha, Yin & Yang, 2016), 'transportation network companies' (TNC) (Shaheen, Chan & Gaynor, 2016) and 'ride-hailing' (Frei, Hyland & Mahmassani, 2017). Throughout this paper, the term 'ride sourcing' for any online transportation is used, since it is the most-used term in top transportation journals (Wang & Yang, 2019). Several studies indicate that the high demand for this transport mode potentially reduces private vehicle ownership and usage (Clewlow & Mishra, 2017; Henao & Marshall, 2019; Rayle *et al.*, 2016). Ride sourcing can also threaten the existence of conventional public transport and taxis (Rayle *et al.*, 2016; Tarabay & Abou-Zeid, 2020). Traffic congestion in urban areas in Indonesia has worsened in recent years due to increased ownership and use of private vehicles (Joewono, Tarigan & Susilo, 2016). It has been suggested that the rise of ride sourcing in metropolitan cities such as Jakarta (Irawan, Belgiawan, Tarigan & Wijanarko, 2019), Bandung (Nugroho, Zusman & Nakano, 2020), and Yogyakarta (Irawan, Belgiawan, Joewono & Simanjuntak, 2020) may contribute to this phenomenon. This only further emphasizes the importance of finding alternative modes of transport that not only reduce traffic congestion but also appeal to the public the way ride sourcing does. Clewlow & Mishra (2017) found that adopters of new transport modes tend to be younger, more educated, and live more in urban areas, which makes students living in large Indonesian cities, in this study Bandung, an ideal target to test new alternative transport modes.

Belgiawan *et al.* (2016) have conducted a study among 500 undergraduates in Bandung and found that factors such as attitude towards cars significantly influence the car ownership decision. Belgiawan *et al.* (2017) and Belgiawan *et al.* (2014) found that apart from attitude, norm factors (peer effects), particularly from peers and parents, have a significant influence on students' intention to own a car. Based on these studies, it can be understood that in order to promote a new transport mode or to encourage students to shift to public transportation, we need to understand what factors significantly influence them to choose a transport mode.

A possible alternative transport mode for students is carpooling (Zhong, Zhang, Nie & Xu, 2020). Zhong *et al.* (2020) state that carpooling has several advantages, such as reducing vehicle miles traveled, alleviating traffic congestion, and saving traveler cost. Students carpooling for campus commuting is not new. It has been successfully implemented on several campuses, for example at American University Beirut (Danaf, Abou-Zeid & Kaysi, 2014), UCLA (Zhou, 2012), UC Berkeley (Riggs, 2015), University of Western Australia (Shannon et al., 2006), Özyegin University Istanbul (Göçer & Göçer, 2019), McMaster University (Sweet & Ferguson, 2019), University of the Basque Country (Gurrutxaga, Iturrate, Oses & Garcia, 2017), Oporto University (Cadima, Silva & Pinho, 2020), University of Auckland (Mohammadzadeh, 2020), and University of Milan as well as Polytechnic University of Milan (Bruglieri, Ciccarelli, Colornia & Luè, 2011). Bruglieri *et al.* (2011) mention that University of Milan and Polytechnic University of Milan implement PoliUniPool, a university carpool service where one of the attributes is expected schedule.

A university-based carpool, where the campus provides the carpool service, like in Milan's case, may be a suitable solution to reduce congestion in Bandung. It can be tested with the students of Institut Teknologi Bandung (ITB), who currently have several commuting alternatives, such as private car, motorcycle, *angkot* (paratransit similar to minibuses in Hong Kong), and ride sourcing (car- and motorcycle-based). Hopefully, new carpool investments can be integrated into urban development because integration of transport infrastructure and urban development, particularly in the Global South, is important (Cervero, 2014). Therefore, this research aimed to understand the commuting mode preferences of students living in boarding houses near ITB when carpooling for their commute is introduced. ITB has two active campuses: the main campus is in the heart of Bandung Metropolitan Area, Jalan Ganeca, Dago and the other one is near the suburban area of Jatinangor, Sumedang. Geographically speaking, as the two campuses are separated by 38 km, the mode of transportation chosen by students who live and actively study in Bandung may be different from those in Sumedang. We realize that the further the distance from ITB, the fewer students live in boarding houses. Therefore, to optimize the carpool service we focused on students who lived less than 10 km from ITB's main campus. To find out the significant attributes and factors that influence students to choose a mode for their daily commute, including carpooling, we conducted a stated-preference survey (Abou-zeid, Ben-akiva, Bierlaire, Choudhury & Hess, 2010; Miro, 2016; Wiryono *et al.*, 2018).

The structure of this paper is as follows. After the introduction, we discuss the stated-preference (SP) method, followed by a discussion of the modeling method used in this study. The next section gives the model result and discussion. Finally, we conclude the paper and discuss the limitations of this study.

Stated Preference Survey

Questionnaire Design

A questionnaire was used to collect the data. The questionnaire was divided into two sections. The first section consisted of an SP survey, using the stated-preference method (Abou-zeid *et al.*, 2010; Miro, 2016). Six alternative transport modes were offered: *minibus*, *car*, *motorcycle*, *car-based ride sourcing* (CBRS), *motorcycle-based ride sourcing* (MBRS), and *carpool* (Wiryono *et al.*, 2018). Minibus refers to PT provided by the government, where at most fifteen passengers can ride in one vehicle. CBRS and MBRS refer to all public transport modes based on online applications (Grab and Gojek). Carpool refers to a new mode of transportation introduced for students who commute from home to campus together with other students.

Every transport mode has different attributes, such as travel time, travel cost, waiting time, transfer amount, access and egress, frequency, congestion time, and parking cost. Travel time is the amount of time (in minutes) needed to travel from the origin to the destination. Travel cost refers to the fare for public transport and fuel costs for cars/motorcycles (in IDR 1,000). Other than car and motorcycle, each transportation mode gives the passenger a different waiting time (in minutes) before the mode arrives in front of the passenger. Minibuses and shuttles have several transfers and a different frequency per hour. Congestion time refers to the time spent (in minutes) during congestion. Access egress time is the amount of time (in minutes) needed for the passenger to walk from his/her house to the carpool or minibus stop and from the carpool or minibus stop to the campus. Baggage cost refers to the price necessary for someone to carry a baggage, which is normally similar to the price of one person to ride a minibus. Finally, parking cost refers to cost of parking on campus (in IDR 1,000). The complete list can be seen in Table 1.

Table 1. Alternatives, Attributes and Their Values in the SP experiment

Attribute	Carpool	Minibus	Car	Motorcycle	CBRS	MBRS
Travel time (min)	4,5,15,17, 18,19	5,6,13	7,8,9,10, 12	4,5,9	7,8,9,11, 12,17	4,5,9
Travel cost (IDR 1K)	8,10,13	3,4,8	1,2,3	1, 2	12,13,14, 15	4,7,8
Number of transfers	0, 1	0,1,2				
Waiting time (min)	5,10	1,2			3,5,7,10	1,3,5
Access and egress time (min)	5,10	4,14				
Frequency (per hour)	2,4,6	13,17				
Congestion time (min)	2,4,5	3,4	2,4,5	1,2,3	2,3,4,5	1,2,3
Parking cost (IDR 1K)			3,6,7	2,3		
Baggage cost (IDR 1K)		4,8				

We developed a number of scenarios, combining each attribute level with an experimental design. The experimental design was a D-efficient design with 24 choice situations in three blocks (Bliemer, Rose & Hensher, 2009). Then we created three types of questionnaires, where each questionnaire had eight scenarios corresponding to the choice situation in each block (ChoiceMetrics, 2018). In the first section, respondents were given the eight scenarios in which the same modes had different attributes. In each scenario they had to choose their preferred transportation mode based on the attributes. The second section of the questionnaire asked about their socio-demographic characteristics, such as age, gender, monthly income, monthly transport vehicle ownership, driving license, and commuting distance (in km).

Data Collection

An online survey tool (Google Form) was prepared for collecting the data. Survey links were distributed across several social media groups (Facebook, Instagram, Twitter, and WhatsApp) and our network of students and colleagues. In addition to the online survey, we also conducted a field survey. The field survey was conducted from July 1, 2018 to July 30, 2018 with the help of ten assistants. For the field survey, the research assistants randomly approached students on ITB campus bringing a tablet computer so that the participants could fill in the online questionnaire directly. First, the participants were asked a filtering question: whether they lived near ITB or not. Those who lived less than 10 km from ITB proceeded to fill out the questionnaire. We provided a gift for those who completed the questionnaire. In total, 177 people (around 0.82% of the total population) participated. Thus, with eight scenarios per respondent, in total 1416 observations were obtained for the discrete choice model.

Descriptive Statistics

The socio-demographic characteristics of the respondents are summarized in Table 2. The first two columns present our sample and the percentage of each category of variables. The final two columns are the total population and its percentage.

Table 2. Socio-demographic Characteristics

Characteristics	Category	Number	Percentage	Population	Percentage
Age	18	7	3.95%	1,168	5.42%
	19	41	23.16%	3,998	18.54%
	20	53	29.94%	4,197	19.47%
	21	23	12.99%	3,545	16.44%
	22	12	6.78%	2,310	10.71%
	23	6	3.39%	1,008	4.68%
	24	8	4.52%	893	4.14%
	25 years old and older	27	15.25%	4,440	20.59%
Gender	Male	98	55.4%	12,288	57.00%
	Female	79	44.6%	9,271	43.00%
Income (monthly)	IDR 0 – 500,000	21	8.5%		
	IDR 500,000 – 1,000,000	40	16.9%		
	IDR 1,000,000 – 2,500,000	71	37.3%		
	IDR 2,500,000 – 5,000,000	35	21.5%		
	IDR 5,000,000 – 7,500,000	6	5.6%		
	IDR 7,500,000 – 10,000,000	1	4.0%		
	More than IDR 10,000,000	3	6.2%		
Expenditure for transport (monthly)	IDR 0 – 500,000	120	67.8%		
	IDR 500,000 – 1,000,000	51	28.8%		
	IDR 1,000,000 – 2,500,000	6	3.4%		
Vehicle ownership	No vehicle	73	41.2%		
	Car	46	26.0%		
	Motorcycle	24	13.6%		
	Car and motorcycle	34	19.2%		
Driving license	No driving license	49	27.7%		
	Car driving license	40	22.6%		
	Motorcycle driving license	26	14.7%		
	Both driving licenses	62	35.0%		
Commuting distance	Commuting distance (km)	Mean: 2.9	Std. Dev: 2.5		

We obtained the population data from the ITB administrators. In ITB, the maximum period of undergraduate study is seven years. Therefore, we categorized the respondents into seven undergraduate years and added one category for graduate students. The graduate students (master and PhD) belong to the category 25 years old and older. The undergraduate students, particularly those in the age of 20, dominated our sample with 30%, followed by age 19 (23%). Our graduate sample was around 15% of the respondents. The next variable was gender. Our sample was dominated by male students, around 55%. If we look more closely, the male proportion was almost the same as in the population, around 57%. Similarly, the age proportions in the sample also matched the population proportion, with some small differences. To reduce the bias, we weighted the sample according to the population age and gender using post-stratified weight as was done in Belgiawan *et al.* (2019).

People older than 20 years are considered adults in most countries. The number of male respondents was slightly higher than the number of female respondents. Most of the students had an income per month between IDR 1 M and 2.5 M (equivalent to US$ 73 and 182). Their monthly expenditure for transport was mostly between IDR 0 and 500 K (equivalent to US$ 0 and 36.5). Most students had no vehicle, nor a driving license for either car or motorcycle. In the last row of Table 2 we present the commuting distance of the respondents. The average distance travelled by the respondents was 2.9 km with a standard deviation of 2.5 km. This means that most of our respondents commuted less than 6.4 km every day.

Non-trading behavior

Non-trading behavior means that whatever the value of the attributes of an alternative choice, the respondents will not make a trade-off by choosing another mode. The result of the non-trading behavior can be seen in Table 3.

Table 3. Non-trading Behavior

Alternative Modes	Number of non-trading	Percentage
Carpool	0	0.00%
Minibus	1	0.56%
Car	7	3.95%
Motorcycle	35	19.77%
Car-based ride sourcing	1	0.56%
Motorcycle-based ride sourcing	19	10.73%
Total	63	35.59%

In one case, the respondent would use a minibus regardless of the attribute values. Most likely this is a captive user of public transport. There was the same case for CBRS. Seven people were non-traders for a car. For motorcycle, private and ride sourcing we can see that they dominate the non-trading behavior, at almost 35% and 19% respectively. Most motorcyclists being non-traders shows that these students are captive users of a motorcycle. This finding is similar with a case study in Yogyakarta, Indonesia, where students tend to use motorcycles often (Herwangi, Syabri & Kustiwan, 2015). Overall, 35.59% of non-traders is a good sign, since the majority prefers an alternative because of the attributes and the attribute values.

Methodology

Mixed Logit Model

The data was analyzed using a mixed multinomial logit model (MXL) with error components. This is a powerful approach, since it can capture the correlation in unobserved variables across alternatives as well as capture unobserved heterogeneity (Train, 2009). In the MXL model, the probability of person *n* choosing an alternative *i* over set of alternatives *j* in scenario *t* maximizes his/her utility (U_{int}) as follows:

$$P_{int} = Pr\left(U_{int} > U_{jnt}, \forall_j \in C_{nt}, j \neq i\right) \tag{1}$$

where C_{nt} is the available choice set, where in our case we had six available alternatives. Those alternatives were: *carpool* (*i* = 1), *minibus* (*i* = 2), *car* (*i* = 3), *motorcycle* (*i* = 4), *CBRS* (*i* = 5), and *MBRS* (*i* = 6). The utility is then decomposed into a deterministic part (the observed part) represented by V_{int}, and a random error (unobserved part) represented by ω_{in} and ε_{int} as follows:

$$U_{int} = V_{int} + \omega_{in} + \varepsilon_{int} \tag{2}$$

The deterministic part of the utility is expressed as follows:

$$V_{int} = \alpha_i + \sum_k \beta_{x_{ki}} X_{kint} + \gamma_n Cost_{int} \tag{3}$$

where $\beta_{x_{ik}}$ is an alternative specific parameter of attribute X_{intk} on the utility of an alternative i for person n in scenario t. α_i is an alternative specific constant (ASC). γ_n is the random parameter for travel cost (represented by $Cost_{int}$), which is assumed to be randomly distributed in order to capture unobserved taste variation of travel cost across individuals. The formula is expressed as follows:

$$\gamma_n = \mu_{Cost_n} + \sigma_{Cost_n}\Omega_{Cost_n} \qquad \Omega_{Cost_n} \sim N(0,1) \tag{4}$$

where, μ_{Cost_n} and σ_{Cost_n} are the mean and standard deviation, respectively, for the cost parameter across the entire sample. γ_n is obtained through simulation by drawing a normal distribution of Ω_{Cost_n}. ω_{in} in represents the random error component specific to person *n* and alternative i. The error components are then obtained by multiplying a standard deviation to be estimated ($\sigma_{\omega_{in}}$) and a random simulated term ($\Omega_{\omega_{in}}$) following the standard normal distribution as expressed in Eq. 5:

$$\omega_{in} = \sigma_{\omega_{in}}\Omega_{\omega_{in}} \qquad \Omega_{\omega_{in}} \sim N(0,1) \tag{5}$$

The probability of the MXL choice is then expressed as follows:

$$P(y|X,\beta,\gamma,\theta,\omega,\Omega) = \int\int\int\int\int\int\int \left(\frac{\exp(U_{int})}{\sum_{j=1}^{C_n}\exp(U_{jnt})}\right) f(\omega_{1n})f(\omega_{2n})f(\omega_{3n})f(\omega_{4n})f(\omega_{5n})f(\omega_{6n})f(\gamma_q)\, d\omega_{1n}d\omega_{2n}d\omega_{3n}d\omega_{4n}d\omega_{5n}d\omega_{6n}d\gamma_q \tag{6}$$

where f (.)s is the probability density function of the random terms and the error components are assumed to be uncorrelated across all alternatives. The log-likelihood with N as the sample size is then as follows:

$$LL = \sum_{n=1}^{N} \ln P(y|X,\beta,\gamma,\theta,\omega,\Omega) \tag{7}$$

The estimation of the model uses maximum likelihood estimation with python Biogeme (Bierlaire, 2016) with 1,000 random draws.

Model Result and Discussion

Mixed Logit Model Results

The result of the MXL model can be seen in Table 4. The first six parameters on the left-hand side is the specific alternative constant, with carpool fixed at 1 as the reference category. A significant constant with a positive sign means that all else being equal the students are more likely to choose that alternative rather than carpool. A significant constant with a negative sign means, ceteris paribus, that the students are less likely to choose that alternative rather than carpool. Car and CBRS are both negatively significant, which means all else being equal carpool is more favorable than those two modes.

Carpool travel time was negative significant, as expected, which means that the increase of carpool travel time will reduce the probability of using a carpool. Conversely, the decrease of travel time will increase the probability of using a carpool. It may be a good thing for the campus to plan a time schedule for the carpool. The second significant attribute was access and egress with a negative value. If a potential passenger reduces the walking time to the carpool stop, it may increase the probability to choose carpool. This means that the campus needs to choose the location of the carpool carefully. Frequency of carpool is significant at 10%, which means that campus needs to consider the number of carpools deployed in one hour. For minibus, the negative significant attributes were congestion time and baggage cost (the last one significant at 10%). The longer a minibus is stuck in a congestion, the lower the probability that students choose minibus. Similarly, the higher the baggage cost, the less likely someone wants to use a minibus. This may be important information for the government to improve the quality of minibuses.

Car travel time was significant with a negative sign, similar to motorcycle travel time. This means that for both private vehicles, the longer the travel time, the less likely it will be that a student uses a car. Likewise, for ride sourcing, both car-based and motorcycle-based, we can observe that the parameters were negative significant. For MBRS, the congestion time was negative significant at 10%. The longer travel time and congestion time significantly reduces the utility of online motorcycles, which means that the respondents would choose motorcycle, since it can travel fast and avoid congestion.

The travel cost parameter was random across individuals. Therefore, in the table we present the mean and standard deviation, represented respectively by mu and sigma travel cost. A negative mu was as expected, however, mu was not significant. The standard deviation of cost on the other hand was significant, which indicates that there was a significant taste heterogeneity of cost across individuals. Finally, for the error components, all except for carpool were significant. These results indicate that there is a substantial amount of preference heterogeneity for mode alternatives with the exception of carpool. The higher coefficient of the motorcycle error component compared to the rest shows that there was a higher heterogeneity in the unobserved effects of motorcycle compared to the other alternatives.

Table 4. MXL Model Results

Attributes	Estimate	Robust t-test		Attributes	Estimate	Robust t-test	
Carpool constant	1	NA		Car travel time	-0.11	-2.02	**
Minibus constant	4.10	1.11		Car congestion time	-0.06	-0.50	
Car constant	-4.11	-2.65	**	Motorcycle travel time	-0.34	-6.88	**
Motorcycle constant	0.96	0.70		Motorcycle cong. time	0.04	0.36	
CBRS constant	-5.10	-3.26	**	CBRS travel time	-0.11	-2.34	**
MBRS constant	-0.49	-0.40		CBRS wait time	-0.04	-0.52	
Carpool travel time	-0.09	-3.14	**	CBRS cong. time	-0.12	-0.29	
Carpool transfer	-0.13	-0.47		MBRS travel time	-0.33	-6.37	**
Carpool wait time	-0.03	-0.30		MBRS wait time	-0.05	-0.97	
Carpool acc. & egg.	-0.14	-3.04	**	MBRS cong. time	-0.21	-1.92	*
Carpool frequency	0.09	1.87	*	Generic parking cost	-0.06	-0.62	
Carpool cong. time	-0.54	-0.33		Mu travel cost	-0.03	-0.66	
Minibus travel time	-0.08	-1.49		Sigma travel cost	0.10	2.39	**
Minibus transfer	-0.04	-0.19		Sigma carpool	-0.46	-1.12	
Minibus wait time	0.05	0.18		Sigma minibus	-0.71	-2.71	**
Minibus acc. & egg.	-0.02	-0.58		Sigma car	3.06	5.33	**
Minibus frequency	-0.14	-1.32		Sigma motorcycle	3.65	10.10	**
Minibus cong. time	-0.97	-2.37	**	Sigma CBRS	-2.28	-2.78	**
Minibus baggage cost	-0.14	-1.67	*	Sigma MBRS	-2.96	-8.89	**
Model Fit							
Number of estimated parameters:				37			
Observations:				1416			
Init log-likelihood:				-2654.46			
Final log-likelihood:				-1317.43			
Likelihood ratio test for the init. model:				2674.05			
Rho for the init. model:				0.50			
Rho bar for the init. model:				0.49			
* significant at 10%; ** significant at 5%							

Value of Travel Time Savings

Another analysis tool that is important for travel demand analysis is the value of travel time savings (VTTS). VTTS can be used to measure how much money (in this case IDR) a person is willing to pay for a unit reduction in travel time (in minute). The VTTS can be measured with the following equation:

$$VTTS_{in} = \frac{\partial V_{in}/\partial Traveltime_{in}}{\partial V_{in}/\partial Cost_{in}} = \frac{\beta_{Traveltime_i}}{\gamma_n} x1{,}000 \tag{8}$$

where $VTTS_{in}$ is the VTTS for person *n* choosing alternative i. ∂V_{in} is the first derivative of the systematic utility. $\partial Traveltime_{in}$ is the first derivative of travel time of person n choosing alternative i. The same can be said for $\partial Cost_{iq}$, which is the first derivative of travel cost. $\beta_{Traveltime_i}$, and γ_n represent the parameters of travel time and travel cost, respectively. Travel time is a specific alternative while travel cost is generic. The VTTS for each alternative is shown in Table 5.

As can be seen in Table 5, the highest VTTS is for motorcycle alternative. A higher VTTS can be interpreted as a person being willing to pay more in order to gain a 1-minute time reduction by using an alternative mode. Thus, the respondents preferred to use a motorcycle to reduce travel time rather than other modes. This was expected, given the traffic conditions near campus. The low VTTS scores for carpool and minibus are a good sign. If we want to promote these modes, we need to increase the quality of their services so that there is a possibility of shifting from motorcycle, the current most popular transport mode, to public transport.

Table 5. Value of Travel Time Savings

Alternatives	Value of Travel Time Savings (willingness to pay)
Carpool	IDR 3,329 / minute
Minibus	IDR 2,778 / minute
Car	IDR 3,988 / minute
Motorcycle	IDR 12,144 / minute
CBRS	IDR 3,955/ minute
MBRS	IDR 11,704 /minute

Demand Elasticities

The calculation of aggregate direct point elasticities was conducted to understand the importance of a particular attribute in determining choice behavior. Direct point elasticity explains the relationship between percentage changes in the magnitude of an attribute of an alternative *i* on the probability of choosing an alternative *i*, as shown in Eq. 9.

$$E_{inX_{kin}} = \frac{\partial P_{in}}{\partial X_{kin}} . \frac{X_{kin}}{P_{in}} = (1 - P_{in}). \beta_k . X_{kin} \tag{9}$$

Since our sample proportion did not match the population proportion, we calculated the aggregate direct point elasticities ($E_{x_k}^{i}$), which account for sampling bias. The formula, adapted from (Atasoy, Glerum & Bierlaire, 2013), is as follows:

$$E_{in_{X_{kin}}}^{W_i} = \frac{\sum_{n=1}^{N_s} w_n P_{in} E_{inX_{kin}}}{\sum_{n=1}^{N_s} w_n P_{in}} \tag{10}$$

where w_n stands for the sample weight for a person n from sample N_s from population N. With this sample weight we can make sure that the relative change in an attribute of a chosen alternative is the same for every individual. The demand elasticity calculation can be seen in Table 5. For the demand elasticity interpretation score, more than 1 means that the particular attribute is elastic, otherwise it is inelastic. Elastic means that a 10% increase of a particular attribute of an alternative's value corresponds to a 10% reduction or more of probability of a person choosing that alternative. Similarly, a 10% decrease of the value corresponds to ten percent or more addition of probability of a person choosing that alternative.

For the demand elasticity calculation, we only took attributes that significantly influenced choice decision, except for travel cost. The travel cost parameter is a generic parameter, but we can measure the elasticity of each alternative. We found that for all alternatives travel cost was inelastic. This means that an increase of 10% in the cost of carpool will only contribute to a 2.7% reduction in the probability of choosing carpool. Apart from cost there were ten significant attributes: travel time (for carpool, car, motorcycle, and online motorcycle), congestion time (for minibus and MBRS), access egress and frequency (for carpool) and baggage cost (for minibus). The demand elasticities for those variables are presented in Table 6.

Table 6. Value of Travel Time Savings and Demand Elasticicies

Elasticities	Carpool	Minibus	Car	Motorcycle	CBRS	MBRS
Travel time	-0.92	NS	-1.08	-1.08	-1.09	-1.33
Travel cost	-0.27	-0.14	-0.05	-0.02	-0.37	-0.11
Access egress	-1.01	NS	NS	NS	NS	NS
Frequency	0.33	NS	NS	NS	NS	NS
Congestion time	NS	-3.10	NS	NS	NS	-0.30
Baggage cost	NA	-0.59	NA	NA	NA	NA

Note: NA = not applicable; NS = not significant

Carpool travel time is inelastic, which means that an increase of 10% of travel time will only correspond to a 9.2% reduction in the probability of choosing carpool. This is different from the other four alternatives, which are elastic, in particular MBRS. This may be a good sign for carpool since whether the carpool travel time is longer (perhaps due to congestion or picking up and dropping off people), it does not have much effect on the probability of choosing carpool. The access egress of carpool is elastic, which means that it is necessary to find proper carpool stops to reduce the access egress time. The frequency of carpool is inelastic, which means one additional carpool in one hour will not have much effect on the decision to choose carpool. Overall, this may be a good sign in view of introducing campus-based carpool, where we need to make sure that access egress time should be reduced.

Minibus congestion time is elastic, which means an increase of 10% of congestion time of minibuses will correspond to a 31% decrease of probability of choosing a minibus. This may be useful information if the government wants minibuses to be better occupied. Baggage, on the other hand, is inelastic. Travel time of MBRS is elastic, which means that a 10% increase in travel time will correspond to a 13.3% reduction of choosing MBRS. This makes sense because people may expect that MBRS can travel faster than other modes. Congestion time for MBRS, however, is inelastic.

Conclusion

Based on our findings, students who live around the ITB main campus do not have high concern over the travel cost they spend. Out of all six traveling modes provided in this study, carpool was a more preferred mode than car and CBRS, which is a good sign in view of providing a carpool service and advocating its usage. There was no significant difference between the carpool constant and minibus, motorcycle and CBRS, which means that those three alternatives are as favorable as carpool for commuting.

Using a private car is not actually preferred by the students when they travel to campus. Therefore, this may offer the local government or public transport providers a good opportunity to promote carpool services for students who live near campus. This is also supported by the result of VTTS and access egress time elasticity for carpool. If there is a possibility to introduce a faster carpool service, there is a possibility that students will shift to using a carpool. Our result imply that minibus providers should improve their quality of service, especially by reducing the time minibuses spend in traffic congestion. For CBRS providers our study provides valuable information and, clearly, they have a large potential market in student commuters.

We realize that this study had shortcomings. We only gathered 177 samples (1416 observations). More samples are necessary to reduce the amount of non-trading behavior, which was around 35.59% in the current study. Also, the error may be reduced by adding more samples. Besides, our findings show that students prefer to use a motorcycle for commuting to campus, while from a safety and security perspective this may be a dangerous choice since there is a higher risk of being involved in a traffic accident for motorcycles compared to cars (Korlantas, 2018).

The same research approach can be utilized for other major cities in Indonesia with large university student populations, such as Jakarta, Semarang, Surabaya, Malang, Makassar, Medan, and Yogyakarta. The idea of transferability of this study is essential to capture the trends toward the commuting mode preferences of students in those cities. The possibility of constructing a generic factorial model for Indonesia is higher when the trend has been mapped in order to improve the commuting mode choice for students. In addition, a future study may include different target samples for variable representation, for example, housewives and workers. Both represent roles embedded in our sample, which would contribute to equivalent and comparable results.

Future research could also be performed by expanding the geographical coverage of our observation by applying the analysis to major cities in neighboring countries, such as Manila, Bangkok, Kuala Lumpur, and Singapore. Different values for traffic congestion, distance, cost, and other attributes may provide different results.

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