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Understanding travel and mode choice with emerging modes; a pooled SP and RP model in Greater Jakarta, Indonesia

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A R T I C L E I N F O

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A B S T R A C T

The research presented in this paper analyzed two data sets Revealed Preference (RP) and Stated Preference (SP), obtained with a new travel diary and mode choice survey. This survey, called Mobility Jakarta, combined both RP and SP parts and was conducted in the Greater Jakarta region. This is the first survey that collected responses from a substantial sample of the whole metropolitan area population. We estimated the discrete choice model pooling SP and RP data sets. We explored the Willingness To Pay, e.g., the Value of Travel Time Savings, and the elasticity for all mode choice alternatives, including On-Demand Transport and Urban Air Mobility.

1. Introduction

Many hours are spent in traffic every day. In Greater Jakarta, commuters are estimated to spend at least three hours daily in traffic. People do not benefit from this unproductive use of their time. The population could use this time for more important, meaningful activities rather than sitting in traffic. This situation occurs not only in Jakarta but in most metropolitan cities around the world. There are, however, a growing number of new mode of transport alternatives available in many cities to tackle this problem. Additional alternatives will surely emerge in the coming years.

One such alternatives is On-Demand Transport (ODT). ODT connects potential passengers and potential drivers through a smartphone app. Growing ODT systems have become popular in many countries. The conventional taxi industry's passenger volume has decreased since the ODT mode of transportation became available (Lam and Liu, 2017). The lower price and the greater convenience of using a smartphone are the main advantages of ODT compared to conventional taxi service. ODT also becomes a link to connect the last miles of a trip to its final destination, especially for motorcycle (MC) ODT, that can move faster through traffic congestion and can drive on narrow roads. These systems have also reduced the number of unemployed (AngryWorkersWorld, 2019). Driver's income was higher than the minimum wage when this system started; however, it has decreased due to the growing number of drivers (Lam and Liu, 2017). Resistance from conventional taxi drivers exists in many countries (Borowiak and Ji, 2019; Lam and Liu, 2017; Peticca-Harris et al., 2018; Rogers, 2018) for various reasons, one of which is the lack of regulations imposed on ODT (Irawan et al., 2019; Rogers, 2018).

Several studies have investigated ODT, both car-based (Dias et al., 2017; Rayle et al., 2016; Young and Farber, 2019) and MC-based

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(Irawan et al., 2019; Medeiros et al., 2018), but they are limited to the characteristics of ODT users and the effects of ODT on other modes. In a study by Dias et al. (2017) on the socio-demographics of respondents that use car-based ODT, it was found that ODT users tend to not only be young, well-educated, and have a higher income, but they also live in higher-density areas. In another study, Rayle et al. (2016) showed that the user characteristics, wait times, and trips served differed between car taxi and car-based ODT. There are few studies on MC-based ODT (see, e.g., Irawan et al., 2019; Medeiros et al., 2018). Irawan et al. (2019) showed that MC-based ODT had a positive effect on the use of public transport when the system becomes a feeder to public transport. They also found that MC taxis and MC ODT competed with each other (Irawan et al., 2019; Medeiros et al., 2018). Other studies found the same competition between car taxis and car ODT (Contreras and Paz, 2018; Habib, 2019).

Another alternative mode is Urban Air Mobility (UAM). There is a growing interest in solving urban transportation problems by using air mobility. Nevertheless, UAM might be suitable only for high-income users because the price is much higher than other alternative modes. UAM may eventually become a realistic alternative mode of transportation. Land transport is indeed insufficient to accommodate the demand for mobility in Greater Jakarta. Three-dimensional transport, such as UAM, may be a strategy to address such congestion. Balac et al. (2019a) noted that several studies were trying to measure the demand for UAM in urban areas (see, e.g., Balac et al., 2019b; Fu et al., 2019; Garrow et al., 2017). Balac et al. (2019b); Balac et al. (2019a) attempted to simulate UAM in the urban transport environment using an agent-based modeling approach based on the potential demand of UAM. Shaheen et al. (2018) measured the potential demand of UAM in several cities in the U.S. using SP experiment and attitudinal questions. In a related study, Eker et al. (2020b) measured individuals' perceptions regarding the potential benefits of UAM.

The developments of Information and Communications Technology (ICT), which enable the evolution of emerging transportation modes, are inevitable. Peer production concepts, also known as a sharing economy in the digital era, have been discussed by Benkler (2002) and Pepić (2018). This business models connects the service offered by a company to individuals through the internet and currently exists in the transportation industry and many other sectors, including hotels, restaurants, ticketing, and e-commerce.

There are several companies in the ODT industry, such as Uber, Lyft, Grab, and Gojek. Uber and Lyft were launched in San Francisco in 2012. Uber focused on a black-car limousine service, while Lyft focused on a long-distance intercity carpooling named Zimride in 2007 (Henao, 2017). Uber was the big ODT player in Southeast Asia before Grab took over its business and Uber began selling its shares. This has also happened in other countries (Sothy, 2019). Currently, the local big players are Grab, which started in 2012 in Malaysia, and Gojek, which began in 2010 in Indonesia. Gojek, which was started from only a MC-based ODT in Indonesia, has expanded into other Southeast Asian markets. Gojek is backed by tech giants like Google and Tencent (Russell, 2018).

Moreover, most ODT companies expanded their businesses by providing other services, including transporting goods, and buying and delivering food. In this way, they also helpedmicro and small businesses to increase their sales (Harsono, 2019). Now that ODT is established, society does not want to reduce its availability. The service is very convenient; people can easily request rides anytime and anywhere and it operates as a door-to-door service with a fixed upfront price. This system is quickly growing as it meets transportation demands when conventional urban transportation modes cannot.

In the future, alternative forms of transportation will continue to emerge, including the development of electric-based or even autonomous vehicles, and flying transportation. Several companies, including Airbus, Uber, and Lilium, have been investing in the development of UAM. Airbus tested the flight of UAM in Eastern Oregon Downing Downing (2019). This system may help the congested city and longer-distance travelers to minimize their travel time. The vertical take-off and landing (VTOL) aircraft, which can land and take-off vertically, may reduce land transportation infrastructure growth in the future. However, the UAM will continue to be more expensive than other transportation alternatives, as its operational cost will be higher.

UAM might face several challenges in the future, however. As mentioned by Ahmed et al. (2020), the sustainability of UAM involves several aspects to be considered, such as safety, training, infrastructure, environment, logistics, cybersecurity, and the human factor. Reiche et al. (2018) and Cohen et al. (2020) also discussed aspects related to the development of UAM, such as challenges, infrastructures, technology, public acceptance, and laws and regulations. Al Haddad et al. (2020) found that safety was the main concern for the adoptions of UAM. Moreover, Eker et al. (2019) found that older persons are relatively more concerned about safety issues related to UAM than younger people.

This research aims to understand and explore the factors that influence mode choice. For each mode of transportation, the study identifies the users, when the transportation is used, the purpose of the trips using that mode of transportation, the trip chains, and the speed to reach different destinations (Jakarta or its agglomeration). We also explore the demand of each alternative: the willingness to pay (WTP) or value travel time savings (VTTS), value travel time assigned to travel (VTAT), and elasticity of all choice alternatives, including ODT and UAM. We conducted a stated choice experiment to gather the data and used discrete choice models for the analysis. The measurement of WTP, VTTS, VTAT, and elasticity all together has rarely been explored by other researchers.

To achieve our objectives, we also conducted a Revealed Preference (RP) survey in Greater Jakarta. Several studies have previously conducted RP surveys to better understand travel behavior (see, for example, Axhausen (1995); Axhausen et al. (2002); Dharmowijoyo et al. (2015)). To observe the WTP from the mode choice experiment, we conducted a Stated Preference (SP) survey. We estimated the model using a pooled RP and SP data set, which allows robust estimates balancing the limitations of both data sets. This study makes several contributions, including:

- We conducted a state-of-the-art RP and SP survey and presented its methodology with a total of 5,143 respondents and 57,524 choice observations.
- We gained new insight into travel behavior in Greater Jakarta.
- We explored WTP, including VTTS, VTAT, and elasticity of all choice alternatives, including ODT and UAM, using pooled SP and RP data.

The remainder of this paper is structured as follows. The second section describes the survey design and data collection. The third section, shows the descriptive statistics of the data in general. The fourth section presents the results obtained from the RP survey. The fifth section describes the SP survey's experimental design and the construction of non-chosen alternatives for the RP data set. The sixth section explores the WTP, the VTTS, and the direct elasticity of choice alternatives using a discrete choice model. The last section of this paper presents the conclusions of the study, and recommendations for further research.

2. Survey design and data collection

The survey was conducted from April to May 2019 in Greater Jakarta, which includes three provinces: West Java, Jakarta, and Banten, comprising 13 cities. The cities outside Jakarta are called Bodetabek (Bogor, Depok, Tangerang, Bekasi). We administered the survey in three waves: The first from April 1 to 13, 2019, the second from April 18 to 26, 2019, and the third from April 29 to the May 9, 2019. Due to Indonesia's 2019 presidential and parliamentary elections, the survey was paused during April 13–17, 2019. A total of 5,143 respondents were interviewed, some of whom represent complete households. To the best of our knowledge, no previous study conducted in Jakarta has used such a large sample size. After data cleaning, the survey consisted of 3,708 respondents in 952 households, 1,432 individual respondents, and 53,977 valid choice observations. The respondents' home location can be seen in Fig. 1.

A paper-and-pencil survey was used for this study, and most of the respondents were willing to fill in the survey form with guidance from the surveyor. The response rate was 50% in the pre-test survey and rose to more than 80% in the main survey, as can be seen in Table 1. This response rate was considerably higher than studies in other countries, for example, Axhausen (2008) for the Swiss experiences. The response rate was high because we approached the informal subdivisions in Indonesia: local communities "Rukun Warga" (RW) and local households groups "Rukun Tetangga" (RT). Each RW consists of approximately five RT, and each RT contains between 30 and 50 household groups. This approach is used to gain respondents' trust by asking permission of the heads of the RW and RT before conducting the survey. The heads of approximately 33 RT were approached, which encompasses about 1,000 households.

Additionally, most surveyors lived in the study area, making it easier for them to approach the respondents directly. A similar approach was also used in Bandung, as briefly explained by Dharmowijoyo et al. (2015). To understand the effort required by the

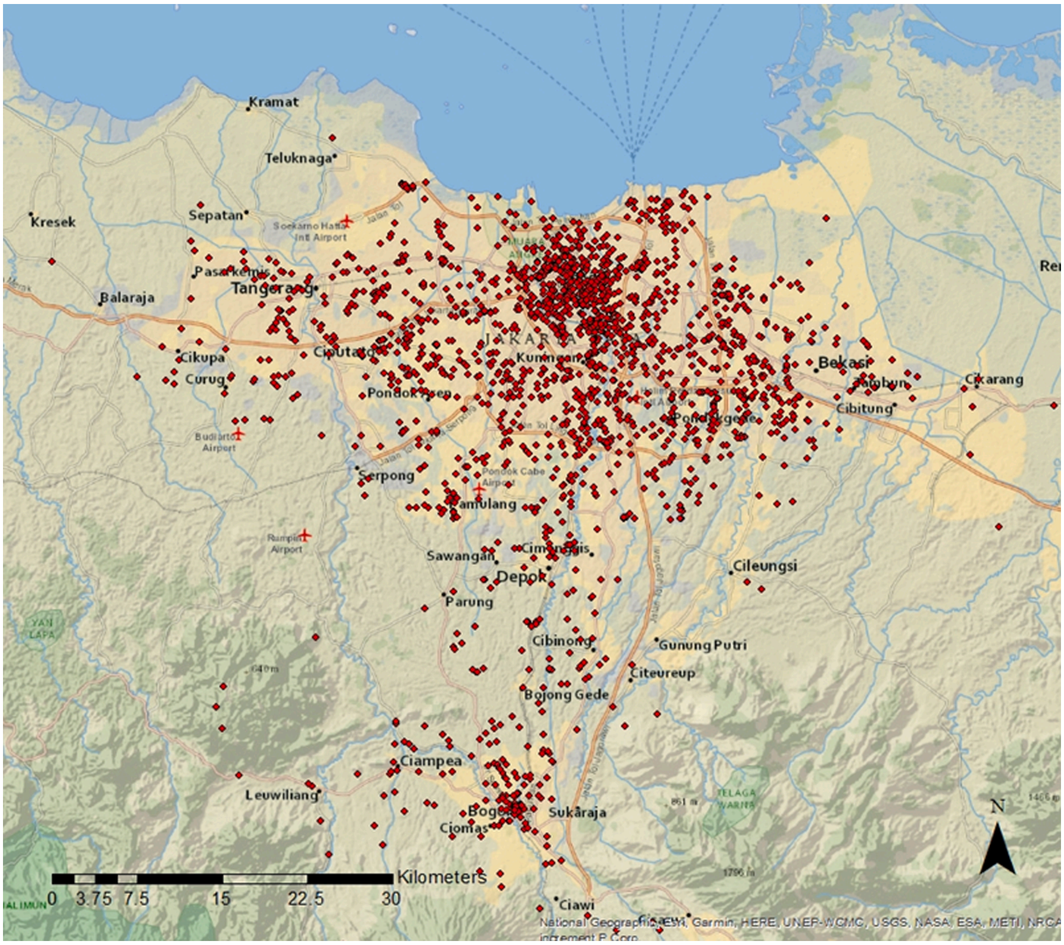


Fig. 1. Home location of respondents in the study area.

Table 1
Response rate of respondents.

Survey	Location	Response rate	Question type	Observation	Response burden
Pre-test	Jakarta	50%	-	-	-
Main survey	Jakarta	87.5%	Socio-demographic	5,143	177
	Bodetabek	98%	RP Survey	37,042	737
			SP Survey	20,482	450

respondents to answer a questionnaire, we estimated the response burden. We found that the response burden for socio-demographic questions was 177 points, 737 points for the RP travel diary survey, and 450 for the SP survey. The method to calculate the response burden was by assigning points to each question type. The scheme is described in Axhausen and Weis (2010) and updated in Schmid and Axhausen (2019). The primary response burden is the address, especially for the RP survey, as respondents are usually unaware of the street numbers in their neighborhood, RT, or RW of their trip destinations. Therefore, the response burden increases with the number of trips. However, the response burden in our survey was relatively low.

The survey included the usual socio-demographic questions, including age, gender, income, car ownership, and the primary mode of transport. The RP travel diary of three working days consisted of detailed information on the respondent's departure time, transport mode, trip destination, and trip purpose. The survey design follows the Mobidrive protocol that was well-designed in Axhausen et al. (2002). The last element in the survey was a mode choice SP experiment. Respondents were asked a couple of preliminary questions before completing the SP experiment, i.e., whether their trips were in Jakarta or not, whether they were a driver or non-driver, and their travel distance. These initial questions reduced the complexity of the choice experiment. For example, in the choice experiment, private vehicle options would not be available for non-drivers. The walking mode option did not exist for trips longer than 1.5 km, and congestion/tolls price variables would not be present for the trips outside Jakarta. The survey included emerging transportation options: ODT MC (Gojek, Grab), ODT car (GoCar, Grab), and UAM. Since the respondents might not know about UAM and might never have seen it before, the surveyor gave a brief explanation of UAM using figures to illustrate its concept. The questions are summarized in Table 2. Public Transport (PT) refers to Bus, Bus Rapid Transit (BRT), train, and angkot (Microbus). An angkot is a microbus with a capacity for a maximum of 12 passengers (Cervero, 1991; Ilahi et al., 2015).

3. Descriptive analysis

Table 3 shows the socio-demographic characteristics of the respondents. The share of male respondents in the sample was slightly higher than in the census (57.30%). About 46.90% of the respondents were younger than 34 years old, which was slightly higher than in the census. 31.70% of the sample had a university degree. More than 90% of respondents live in a single-family house and own the house; this is expected as the apartment share of the housing market is less than 2% (Yudis, 2019). However, the number of respondents who are homeowners overrepresented, as other sources suggest that it should be around 47.85% (BPS, 2019). House prices in Indonesia are relatively affordable, and thus ownership does not necessarily suggest that owners have high incomes. Furthermore, a house can be inherited from previous generations, depending on the size and location. The most likely homeownership arrangement is that the owners have a mortgage for the house from a bank based on the husband and wife's joint income.

Jakarta City tends to have high rise buildings in the center and then low-rise buildings towards the city's outskirts, making the city more spread out and expensive to maintain or invest in infrastructure. Around 41.60% of respondents drove in Jakarta, and 28.60% drove in the urban agglomeration. The shares of the main modes of transportation, or the most frequently used, can be seen in Table 3. The number of ODT or ride-sourcing users was substantial. We found that MC had the highest share (54.30%), followed by car (15.30%), MC ODT (10.90%), and public transport (bus, BRT, commuter rail, microbus) (9.9%).

4. Revealed preferences

4.1. Mode choice by socio-demographics, trip purpose, and distance

The mode choice was different from eight years ago when Japan International Cooperation Agency conducted travel diary surveys (JICA, 2012). It was mainly influenced by the spread ICT and the ODT arrival in Greater Jakarta. The chi-square tests shown in Table 4 and Table 5 indicate a significant relationship between the chosen mode of transportation and the respondents' socio-demographic attributes. In general, those younger than 24 dominated all modes, as the number of those persons in Indonesia was dominant. Around 66.7% of MC ODT users and 33.7% of car ODT users were less than 24 years old. This number was equal to 6.5% of all trips. The majority of car and MC ODT users were female. Similar findings were previously reported in Canada, where most ride-hailing users were young and female (Young and Farber, 2019).

The users of PT (bus, BRT, and train) usually do not have access to a car, but they are more likely to have access to a MC. Angkot users, on the other hand, have access neither a car nor a MC. Less than 10% of the respondents are more likely to take ODT or conventional taxis. Cars were more likely to be used by full-time workers and university degree holders. The MC was more likely to be used

Table 2
The survey questions.

Socio-demographics	Travel diary	Choice alternatives
Age	Destination	Walk
Gender	Mode transport	Car
Income	Departing time	MC
Expenditures	Arrival time	Public transport
Address	Address	Car ODT
Number of households	Trip distance	MC ODT
Vehicle ownership	Transport cost	Car Taxi
License	Frequency activity	MC Taxi
Access to private vehicles	Type of activity	UAM
Main mode		
Education		
Occupation		
Dwelling		
Working hour		

by persons with a monthly income less than IDR 18 million (1,250 USD)[1], and the car is more likely to be used by those with an income higher than IDR 18 million.

The mode choice of the respondents depends on the purpose of the trip. Overall, users preferred private vehicles for all trip purposes. The results showed that public transport share increases for a return home and work trip purpose, while the choice of ODT increased for education and leisure trip purposes. Walking was more frequently used for work, daily shopping, and religious activities. Respondents were more likely to use MC, followed by car, walking, and MC ODT for morning, afternoon, and evening trips. However, respondents were more likely to walk, followed by using MC, at midday. At night, respondents preferred to use MC, followed by car and walking.

As can be seen in Fig. 2, for short distances (0 to 1.5 km), the share of Non-Motorized Transport was the highest, which refers to walking and use of a bike. However, when the distance increased, the share of private vehicles increased. Interestingly, conventional taxi share was lower than the ODT. Certainly, ODT was more convenient than a conventional taxi, as people could have an upfront price estimate, a lower price, and faster service. People prefer to use ODT rather than a conventional MC taxi because, in the case of the latter, they must first negotiate the price with the driver. MS ODT was used not only for short distances but also for long distances. The share of MC ODT was greater than 12% when the distance was farther than 5 km.

The public transport share more than doubled when the distance was more than 30 km, because access to private vehicles is insufficient for people who live far from their destinations. People who live farther from activity locations have a relatively lower income level, and they cannot afford to live in places with a shorter commute. Moreover, the price of public transport is lower than other modes due to government price subsidies, especially for BRT and train.

4.2. Cost price structure of the transport modes

Fig. 3 shows the price structure of the different modes of transportation, presented in a log-time and log-cost scale format. These figures are based on the travel cost and travel distance for each trip of the respondents. Blue represents car-based modes, orange represents MC-based modes, and green represents the public transport modes. It shows that public transport modes have a lower cost in general. When the distance increases, the price of public transport is lower than car-based or MC-based modes. Compared to other public transport modes, the lower themarginal price of traveling by traindecreases by distance. For car-based modes, it can be observed that traveling by car is inexpensive for short-distance trips, but it becomes the most expensive mode for longer trips. Car ODT prices are higher than those of conventional car taxis as reported by the respondents. Regarding the price of MC-based modes, we can see that the price of MC taxis is the highest, followed by MC ODT and MC.

4.3. Trip chains

Each trip had a particular purpose: work (w), to go home (h), education (e), errand (er), leisure (l), and daily and special shopping (s). Trips for religion and other purposes are combined into leisure purposes, and drop-offs are considered to be errands. Table 6 shows the 10 most frequent trip chains that make up 94.52% of all activity chains. The most frequent chain is home-work-home (h-w-h), followed by home-education-home (h-e-h). The result shows that these simple mandatory activity chains have a share of 55.81%, which is considerably higher than the results in other countries, Schlich et al. (2004) report this share to be less than 25% in the case of Mobidrive and Uppsala. Following these two chains, the home-shopping-home (h-s-h) trip chain is the third most common with 9.52%.

We also divided the trip chains based on gender and household monthly income categories. Males had a higher share for most trip chains; however, females had a higher share of home-shopping-home, home-leisure-home, and home-errand-home trip chains. It showed that transport for shopping, leisure, and errand purposes was more likely to be taken by females because they are less likely to

[1] USD 1 is equal to IDR 14,400

Table 3
Descriptive statistics of the survey respondents.

Variable	Overall (%)	Household (%)	Individual (%)	Census (%)
Male	57.30	51.10	73.40	50.70
Female	42.70	48.90	26.60	49.30
Age categories				
Younger than 24 years old	46.90	45.70	50.00	44.09
Aged 24–29 years old	11.30	7.30	21.60	9.19
Aged 29–34 years old	6.30	5.30	9.10	9.10
Aged 34–39 years old	8.30	7.90	9.10	8.44
Aged 39–44 years old	8.80	10.60	4.30	7.39
Aged 44–49 years old	9.20	11.20	3.90	6.20
Aged 49–54 years old	5.30	6.80	1.50	5.01
Older than 54 years old	3.90	5.10	0.60	10.54
University degree	31.70	27.60	42.50	-
Owned house	92.40	95.10	85.40	47.85
Single-family house	97.20	99.10	92.30	-
Has access to car	25.60	23.80	30.20	-
Has access to MC	67.90	60.00	88.50	-
Driving license				
Car	5.60	5.10	7.00	-
MC	41.00	35.50	55.10	-
Car and MC	23.40	23.40	23.40	-
No license	30.00	35.90	14.50	-
Working hour				
Full time	32.50	27.60	45.30	-
Half-time (30 h)	11.60	10.10	15.60	-
Half-time (20 h)	13.40	13.80	12.30	-
Student	29.20	31.10	24.50	-
Non worker	13.20	17.50	2.30	-
Saving (%)				
0–25	23.20	19.10	33.90	-
25–50	24.00	27.60	14.50	-
50–75	38.10	38.40	37.60	-
75–100	14.70	15.00	14.00	-
Transport cost (%)				
0–25	79.40	78.60	81.60	-
25–50	14.70	15.60	12.20	-
50–75	0.80	1.00	0.50	-
75–100	5.10	4.80	5.70	-
Type of respondents (%)				
Driver in Jakarta	41.70	39.60	47.00	-
Driver in agglomeration cities	28.50	32.60	17.90	-
Non-driver in Jakarta	11.60	13.40	7.10	-
Non-driver in agglomeration cities	18.20	14.40	27.90	-
Main mode of transport (%)				
Walk	6.70	8.40	2.30	-
Bike	0.70	0.80	0.60	-
Bus	0.60	0.50	0.90	-
BRT	1.20	0.70	2.70	-
Commuter rail	3.70	1.40	9.60	-
Microbus (angkot)	4.40	5.60	1.10	-
Car	15.30	15.80	14.00	-
MC	54.30	51.90	60.50	-
Car taxi	0.01	0.01	0.01	-
Car ODT	1.10	1.30	0.60	-
MC taxi	1.00	1.30	0.30	-
MC ODT	10.90	12.30	7.30	-

be employed. The income categories also influenced the trip chains of respondents. The income was divided into three-levels: low income (less than IDR 5 million), medium-income (between IDR 5 and 15 million), and high income (more than IDR 15 million); medium-income respondents had higher shares for all trip chains, but lower-income respondents had a higher share for h-w-l-w-h and h-er-h trip chains.

4.4. *Speed by distance, mode, and region*

The average speed of modes increased with the traveled distance, as can be seen in Fig. 4. We calculated the speed based on respondent's reported travel time and distance. The calculation is based on the aggregate of all stages and modes used. For short distances, the speed was slower due to the frequent walking and bike use. Fig. 5 presents the speed for different modes in Jakarta and its

Table 4
Socio-demographics of the respondent by chosen mode of transport.

Attributes	Walk	Bike	Bus	BRT	Train	Angkot	Car	Car Taxi	Car ODT	MC	MC Taxi	MC ODT
Row percentage	18.80	0.50	0.60	0.90	3.00	3.80	13.50	0.10	1.00	47.30	1.10	9.50
Male	59.42	59.89	64.56	34.78	74.73	29.92	65.52	54.55	18.38	66.48	19.11	34.60
Age(years)												
< 24	32.34	58.76	55.34	61.18	41.37	38.05	26.40	50.00	33.70	50.01	34.49	66.69
24–29	17.32	3.39	17.96	15.53	32.12	9.55	8.42	20.45	4.74	12.52	8.68	6.65
29–34	10.40	5.65	6.31	5.59	9.96	7.99	5.60	0.00	1.95	7.49	5.46	3.00
34–39	11.71	10.17	3.40	7.45	5.69	16.9	8.90	2.27	4.46	8.20	11.41	6.28
39–44	9.90	0.00	2.43	5.59	5.96	11.24	15.70	0.00	9.75	7.49	16.38	5.20
44–49	8.49	10.73	8.74	2.48	3.29	8.84	16.84	13.64	13.37	7.78	13.90	4.65
49–54	4.11	6.78	2.91	2.17	1.07	3.54	11.90	13.64	15.32	4.15	5.96	4.31
> 54	5.74	4.52	2.91	0.00	0.53	3.89	6.24	0.00	16.71	2.35	3.72	3.23
University degree	33.18	9.04	43.20	43.48	28.38	11.17	57.88	36.36	37.05	30.67	8.44	25.66
Owned of house	87.79	100.00	97.57	84.16	89.23	95.19	97.58	86.36	96.10	92.15	82.38	91.98
Has access to Car	15.32	3.39	21.36	20.19	11.74	5.16	85.10	6.82	29.25	16.82	7.69	14.24
Has Access to MC	61.21	18.64	66.02	53.73	85.50	26.10	55.20	70.45	45.13	87.95	22.33	33.60
Full-time	30.15	20.90	38.83	41.30	66.64	13.58	50.50	22.73	20.89	32.74	12.90	20.30
Half-time (30 h)	21.22	12.99	11.17	13.04	9.61	7.64	13.38	27.27	5.57	12.73	4.96	7.62
Half-time (20 h)	17.75	6.78	19.42	8.07	12.54	23.34	11.60	13.64	15.04	15.27	8.68	9.45
Student	11.77	44.63	22.82	37.27	9.88	19.80	18.92	31.82	24.51	29.73	24.32	50.39
Unemployed	19.12	14.69	7.77	0.31	1.33	35.64	5.60	4.55	33.98	9.53	49.13	12.25
Driving license												
Car	4.62	0.00	2.91	9.32	1.51	0.21	23.96	0.00	10.58	2.00	1.99	5.60
MC	42.74	16.38	20.87	23.60	66.46	18.10	7.14	29.55	12.53	60.61	7.69	41.00
Car and MC	9.41	3.95	36.41	19.88	10.05	2.76	60.98	29.55	15.60	20.91	2.98	23.40
No license	43.24	79.66	39.81	47.20	21.98	78.93	7.92	40.91	61.28	16.48	87.34	30.00
Start time												
Morning (4-9am)	10.72	0.59	0.69	1.06	3.47	4.52	13.81	0.14	0.63	53.56	1.26	9.57
Midday (9am-2 pm)	49.15	0.51	0.25	0.30	0.73	4.04	7.48	0.09	1.31	26.48	1.92	7.74
Afternoon (2 pm-7 pm)	8.75	0.31	0.59	1.06	3.94	3.15	15.67	0.12	1.08	54.54	0.44	10.35
Evening (7 pm-12am)	9.21	0.68	0.75	0.75	4.47	1.42	24.32	0.07	1.56	45.53	0.07	11.18
Night (12am-4am)	16.67	0.00	0.00	0.00	0.00	0.00	27.08	0.00	0.00	54.17	0.00	2.08

Chi-squares tests (X^2) are all significant ($p-value < 0.001$).

Table 5
Income, trip distance, and trip purpose of the respondent by chosen mode of transport.

Attributes	Walk	Bike	Bus	BRT	Train	Angkot	Car	Car Taxi	Car ODT	MC	MC Taxi	MC ODT
Income (IDR Million)												
< 1	18.13	0.16	0.00	0.90	2.71	7.38	4.68	0.57	0.08	58.90	1.56	4.92
1–3	29.97	1.04	0.86	1.43	2.32	9.56	2.94	0.27	0.48	44.34	0.83	5.97
3–5	27.15	0.01	0.59	0.47	5.59	4.67	4.75	0.10	0.31	49.15	1.17	6.04
5–8	20.97	0.44	0.53	1.21	3.96	4.22	10.43	0.05	0.20	50.36	1.66	5.98
8–12	16.07	0.74	0.68	0.25	1.16	2.09	17.50	0.00	0.91	46.62	0.42	13.56
12–15	5.96	0.81	0.23	1.12	1.41	1.27	22.42	0.00	1.41	49.19	0.40	15.77
15–18	5.08	0.95	0.40	0.95	0.00	0.71	26.19	0.00	2.22	47.62	0.95	14.92
18–21	5.69	0.00	0.71	1.00	0.85	0.43	28.31	0.85	5.19	34.85	1.21	20.91
21–25	2.54	0.00	1.14	0.76	0.38	0.76	42.39	0.00	1.52	37.31	0.51	12.69
25–28	4.43	0.95	0.48	1.11	0.79	0.48	35.79	0.16	4.59	31.67	1.82	17.74
>28	4.90	1.18	0.00	1.76	0.20	0.39	42.55	0.00	5.29	30.39	0.39	12.94
Trip purpose												
Go home	9.99	0.52	0.58	0.88	3.44	4.34	14.84	0.12	1.09	52.29	1.18	10.73
Drop off	18.39	0.15	0.73	0.00	0.15	9.64	13.14	0.00	2.77	50.22	0.73	4.09
Work	18.54	0.16	0.76	0.96	4.68	2.44	17.07	0.12	0.35	48.34	0.54	6.04
Education	8.00	0.84	0.49	1.54	1.23	3.44	9.33	0.18	0.62	54.82	0.99	18.52
Daily shopping	32.89	1.39	0.28	0.00	0.42	9.99	4.16	0.21	1.80	33.59	6.32	8.95
Special shopping	20.46	0.53	0.00	0.00	1.06	9.17	16.58	0.18	3.35	39.68	1.23	7.76
Leisure	17.56	0.47	0.16	0.79	1.27	6.33	17.72	0.00	6.65	36.08	1.42	11.55
Religion	88.55	0.51	0.00	0.00	0.30	0.30	1.82	0.00	0.61	6.38	0.00	1.52
Other purpose	78.82	0.35	0.06	0.40	0.40	0.17	2.94	0.00	0.40	14.95	0.06	1.44

Chi-squares tests (X^2) are all significant ($p-value < 0.001$).
1 USD is equal to 14,085 IDR on 31th of July 2019.

agglomeration. The speed of the transport modes was different for each mode and region. The average speed of bike, bus, BRT, angkot, MC Taxi was higher in the agglomeration; however, the average speeds of the other modes were quite similar. In general, the agglomeration had a higher speed than Jakarta due to lower traffic congestion.

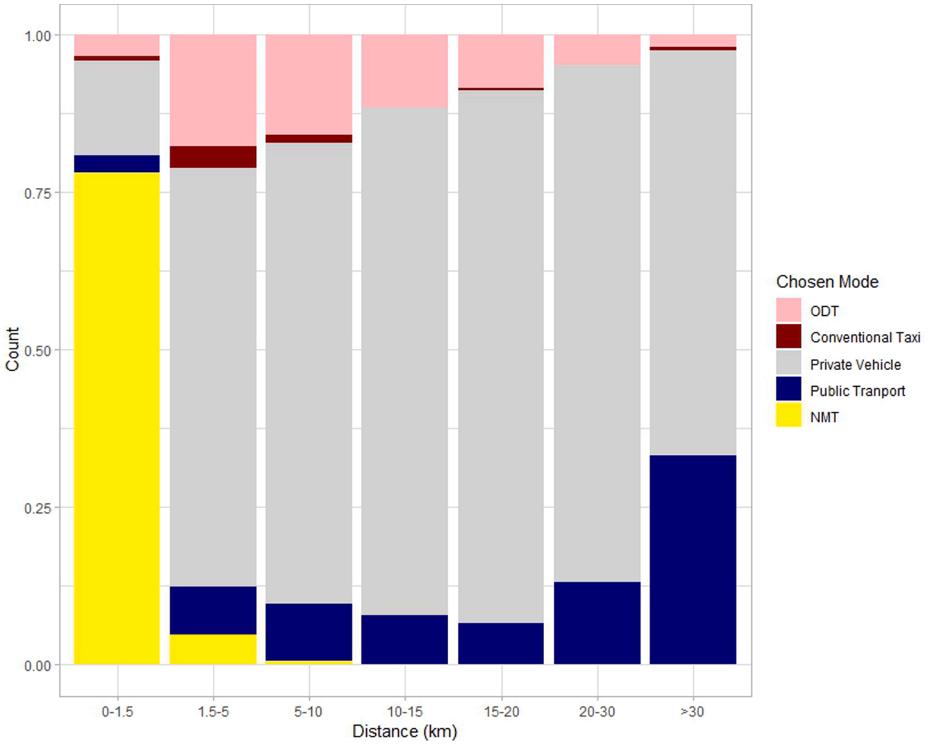


Fig. 2. Travel distance by mode.

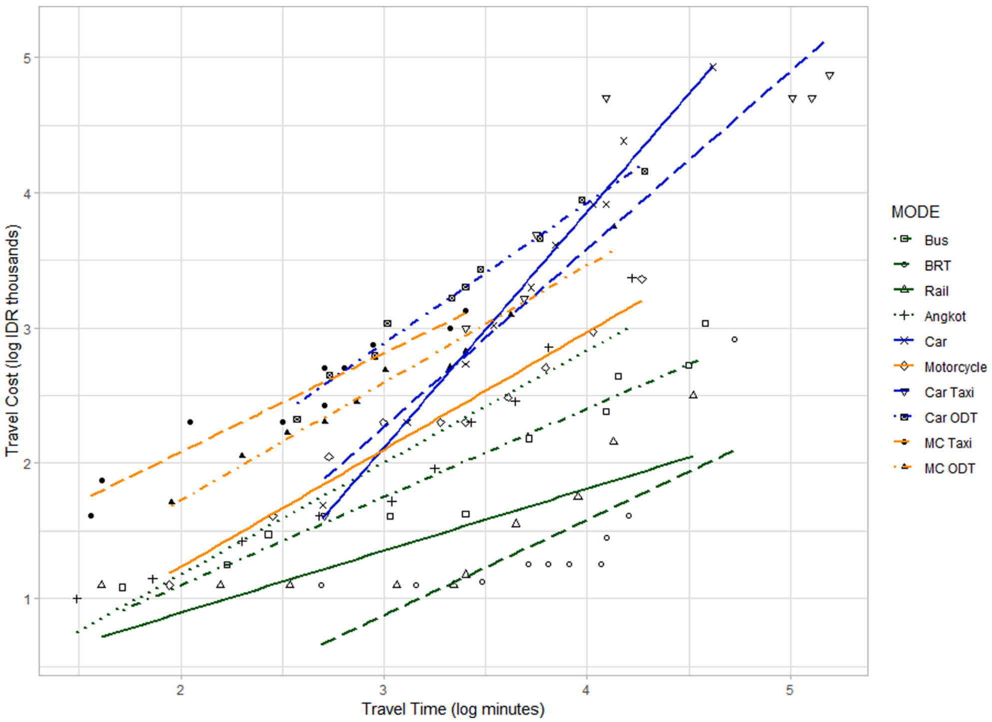


Fig. 3. Travel time (log) and travel cost (log) by mode.

Table 6
Income, trip distance and trip purpose of respondent by mode of transport.

Trip chains	Male	Female	Low Income	Medium Income	High Income	Total
h-w-h	67.60	32.40	32.37	51.14	16.49	39.79
h-e-h	54,56	45.44	25.23	52.91	21.87	26.02
h-s-h	11.00	89.00	31.44	53.11	15.45	9.52
h-w-l-w-h	77.92	22.08	59.05	40.44	0.51	7.69
h-l-h	35.23	64.77	32.72	41.72	25.56	4.91
h-w-l-h	84.62	15.38	45.16	53.11	1.74	2.64
h-er-h	33.63	66.37	47.66	39.77	12.57	2.23
h-e-l-h	58.82	41.18	41.18	47.06	11.76	0.66
h-s-w-h	96.74	3.26	26.09	73.91	0.00	0.60
h-w-s-h	55.07	44.93	37.68	47.82	0.51	0.45
Row percentage	57.20	42.80	33.30	50.30	16.40	94.52

Chi-squares tests (X^2) are all significant ($p - value < 0.001$).
1 USD is equal to 14,085 IDR on 31th of July 2019.

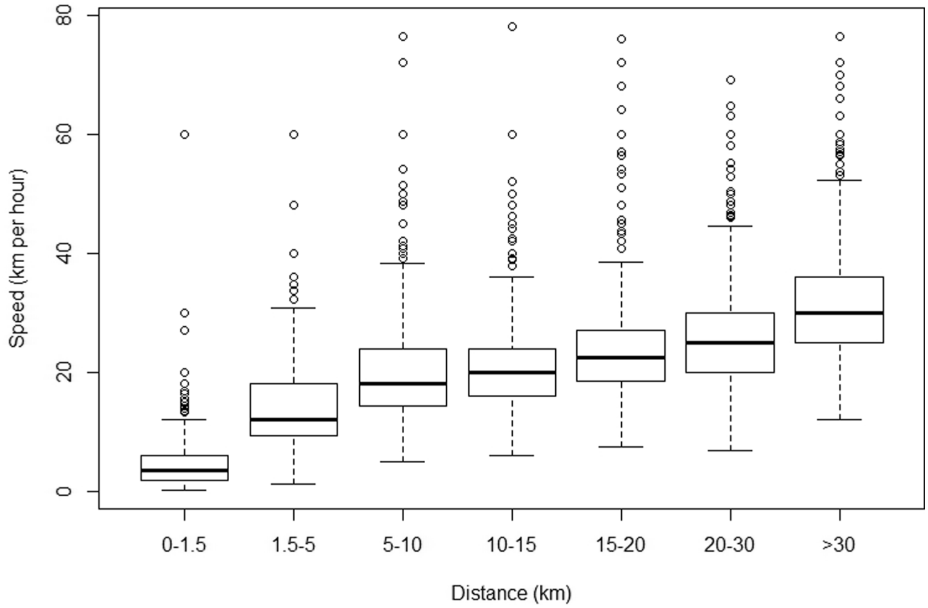


Fig. 4. Mode speed by distance.

5. Constructing choice alternatives from Stated Preference (SP) and Revealed Preference (RP)

5.1. SP data set: Experimental designs

We constructed stated choice experimental designs with a D-efficient design using Ngene (ChoiceMetrics, 2014). All the respondents of the RP survey, equaling 5,143 respondents, were given SP surveys. The mode choice experiment in Greater Jakarta was categorized by travel distance to the place of their daily activities, driver or non-driver, traveling inside or outside of Jakarta. The respondent received preliminary questions about these categories. The mode alternatives and variables were based on the respondent's answers to the preliminary questions. Each respondent received four-choice experiments. In total, there are 20,064 observations.

The types of experiments are shown in Table 7. The congestion/toll charging attribute was only available for the respondent who travelled within or to Jakarta. There are nine different modes, including walking, PT, car, MC, car Taxi, MC Taxi, MC ODT, car ODT, and UAM. Walking was only available for a distance less than 1.5 km and applicable for drivers or non-drivers. The car and MC were always available in each distance interval, but not available for non-drivers. To reduce the complexity of the choice alternatives, we assigned ODT and conventional taxi at random, meaning that for some respondents, "Taxi" appeared, and for some respondents, "ODT" appeared as a choice option. For the access time, we assume a range of 5 min, 10 min, and 15 min to get from the station or shelter to vertiports. The detail of the attributes can be seen in Table 8. We ensured that the travel time and travel cost offered produced VoT values within the range found in the paper by Belgiawan et al. (2019b). For car-based modes, the car VoT was the highest in the survey design, followed by conventional car taxis and car ODT. Then, for MC-based modes, the MC VoT was the highest, followed by MC taxis and MC ODT. The VoT offered for UAM was the highest compared to other modes because UAM has the fastest travel time and

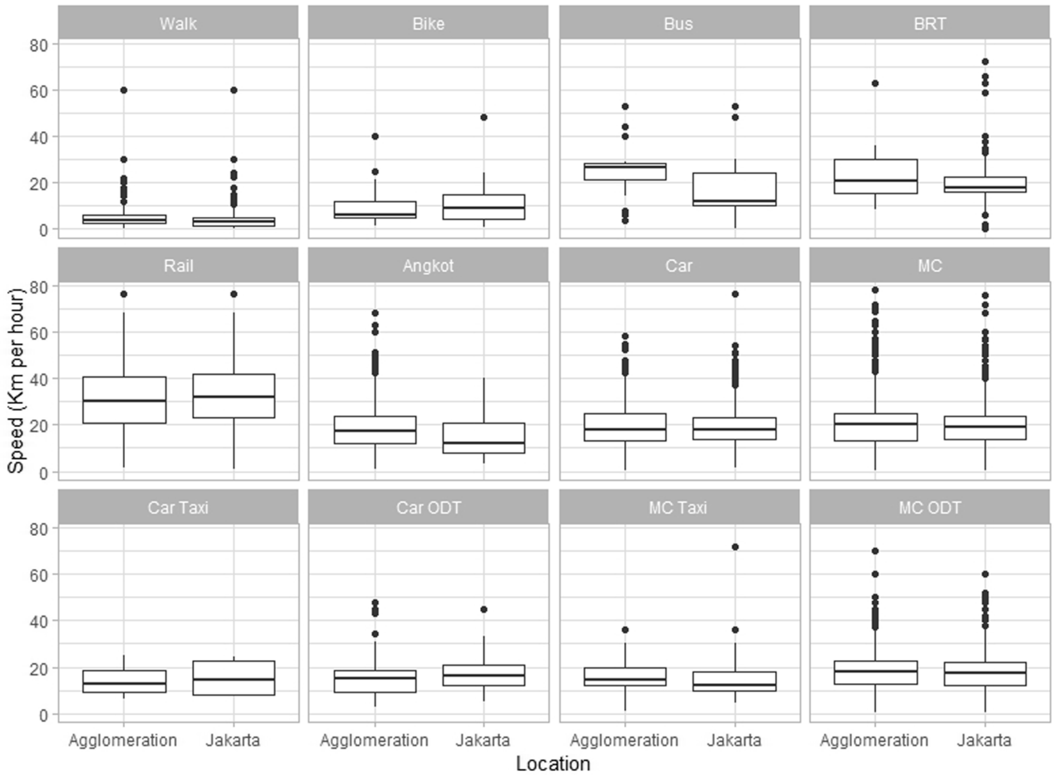


Fig. 5. Mode speed in different regions.

Table 7
Availability by mode of transport, distance, and driving ability.

Mode	0–1.5 km	1.5–5 km	5–15 km	15–25 km	>25 km	Driver	Non driver
Walk	True	False	False	False	False	True	True
PT	True	True	True	True	True	True	True
Car	True	True	True	True	True	True	False
MC	True	True	True	True	True	True	False
Car Taxi	Random	Random	Random	Random	Random	Random	Random
Car ODT	Random	Random	Random	Random	Random	Random	Random
MC Taxi	Random	Random	Random	Random	Random	Random	Random
MC ODT	Random	Random	Random	Random	Random	Random	Random
UAM	False	False	True	True	True	True	True

the highest cost. The assumptions of the cost per km of UAM in this scenario varied between USD 0.69–2.08[2]. However, if we account for the value on purchasing power parity (PPP)[3] in 2019 (OECD, 2019), the cost is around 2.1–6 USD/km. Uber Air expects to have a cost of around 5.73 USD per mile/3.5 USD/km and hopes to reduce the price to 1.15 USD/km and even to 0.27 USD/km in the long-run (Dickey, 2020). Neighboring Singapore expects the cost to be around 3.75 USD per mile/2.3 USD/km or double the price of ground car raid-hailing (TheJapanTimes, 2019). Therefore, we tried to cover that range of costs in our scenarios.

5.2. RP data set: non-chosen transport alternatives

The non-chosen transport alternatives for each trip were constructed based on information from google API (Google, 2019b). We collected the coordinates of each trip origin and destination based on geocoding Google API. Then we collected the information of non-chosen alternatives: transit, driving, and walking based on Google API direction (Google, 2019a). We report the travel time information of each non-chosen alternative mode available on the exact departure time reported in the survey. For bike and MC, however,

[2] USD 1 is equal to IDR 14,400
[3] USD 1 is equal to IDR 4,753

Table 8
Attributes of each mode of transport and category.

Attributes	PT	Car	MC	Car Taxi	MC Taxi	Car ODT	MC ODT	Walk	UAM
Travel cost (Thousand IDR)									
0–1.5 km	3;6;8	6;8;10	2;4;6	12;14;16	5;10;15	7;12;15	6;10;12	-	-
1.5–5 km	6;12;17	14;18;20	9;10;13	25;30;40	15;20;25	14;25;35	15;18;22	-	-
5–15 km	9;18;27	22;28;32	13;20;25	58;90;110	30;35;45	55;80;100	25;35;40	-	60;100;150
15–25 km	13;30;55	35;60;75	20;30;45	75;120;160	50;65;80	72;110;145	45;55;68	-	150;200;250
>25 km	20;40;65	62;90;115	30;40;50	110;170;250	72;90;120	105;165;220	65;80;96	-	250;300;350
Travel time (minute)									
0–1.5 km	5;10;16	6;12;15	4;6;8	6;10;15	6;7;8	6;8;10	4;6;8	30;50;70	-
1.5–5 km	10;20;30	10;20;30	8;15;25	10;20;25	9;15;20	10;20;30	10;15;25	-	-
5–15 km	15;30;45	15;30;45	15;25;35	25;40;55	15;25;32	25;40;55	15;25;32	-	8;9;10
15–25 km	30;45;60	37;60;70	25;40;50	35;55;70	25;40;50	35;55;70	25;40;50	-	10;12;15
>25 km	35;60;90	52;90;120	27;50;70	52;75;100	35;60;70	105;165;220	35;50;70	-	13;17;23
Transfers	Yes;No	-	-	-	-	-	-	-	-
Waiting time (minute)	5;15;30	-	-	5;10;20	5;10;20	5;10;20	5;10;20		10;15;25
Toll/congestion charging (Thousand IDR)	-	10;15;25	5;10;15	10;15;25	5;10;15	10;15;25	5;10;15	-	-
Access time (minute)	5;10;15	-	-	-	-	-	-	-	5;10;15

1 USD is equal to 14.400 IDR on 25th of May 2019.

there was no Google information available for travel time and limited research regarding the speed of these modes of transport are in urban settings. We thus assume that a MC's speed is 3.3 km/h faster than that of a car (Walton and Buchanan, 2012). For a bike, the speed depends on the age of the respondents. The speed of an older person was 10 km/h, while a younger person's speed was 15 km/h (City of Copenhagen, 2013; Woodcock et al., 2018). We assumed each mode's travel cost based on the travel prices that exist in Greater Jakarta.

The detail of the assumptions can be seen in Table 9. There were no costs related to walking or biking. The base in the parameter travel cost indicates the travel cost when the respondent first begins to use the mode. We collected waiting time, transfer, and walking time for transit based on the Google API. There was no specific API for each different transit mode. The mode was not always available. For example, if the respondents did not have access to cars and MC, those modes would not be available as a non-chosen alternative. The waiting time for an angkot, ODT, and a conventional taxi was five minutes. The access walking time of angkot or microbus was five minutes, and transfers only occur when the trip was longer than 10 km.

5.3. Description of the pooled SP and RP data set

Our data set contains 52,731 observations, excluding microbus alternative. The share of MC choices from the SP and RP data set is the highest. As shown in Fig. 6, the share of choice alternatives varies by age group and income group.

6. Modeling framework

We employed the multinomial logit (MNL) and mixed logit (MXL) formulation for the choice modeling analysis, both of which are widely used for policy analysis. We used 1,000 Halton draws for MXL. The estimation took seven days. This paper used the R package, mixl, to estimate the model (Molloy et al., 2019). The model that we presented here was based on pooled SP and RP data sets. Train (2003); Cherchi and Ortúzar (2011); Schmid et al. (2019) show that the pooled SP and RP data sets have a better estimation and robustness, which could improve the quality of only the SP or RP data sets. MNL assumes that the error term ε is equally Identical and Independently Distributed and that the alternatives have the same probability distribution and independence (McFadden, 1973; Train, 2003). The alternative specific constants (ASCs) are decomposed into their mean value and their standard deviation, denoted by $\eta_{i,n}$. The utility of a person n choosing alternative i in choice situation t can be seen in Eq. 1 for MNL and Eq. 2 for MXL.

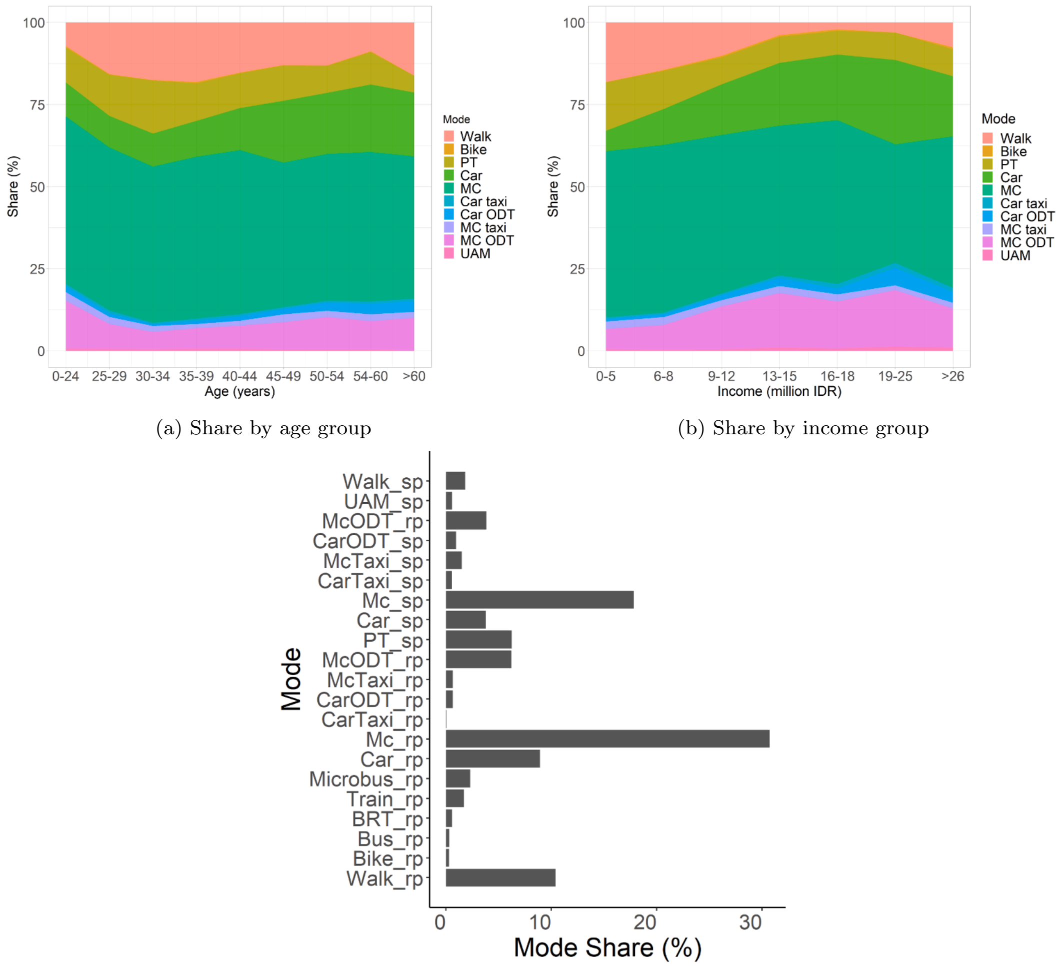
$$U_{i,n,t} = ASC_i + \beta_i X_{i,n,t} + \varepsilon_{i,n,t} \tag{1}$$

$$U_{i,n,t} = (ASC_i + \eta_{i,n}) + \beta_i X_{i,n,t} + \varepsilon_{i,n,t} \tag{2}$$

There are 11 alternatives in Model 1 and 8 alternatives in Model 2 and Model 3. MC-based and car-based taxis were converted to taxi, and MC-based and car-based ODT were converted to ODT. The utility formulation for choice alternatives $i \in \{walk, bike, \ldots, UAM_{SP}\}$ and individual $n \in \{1, 2, .., N\}$ in choice scenario $t \in \{1, 2, \ldots, T\}$ can be seen in the Appendices. Travel cost has a continuous interaction term with income and travel distance. In the meantime, the travel time of UAM has a continuous interaction term with travel distance, which corresponds to elasticity λ_{Income} and $\lambda_{Distance}$ (Ilahi et al., 2019; Vrtic et al., 2010; Mackie et al., 2003). *Income* refers to the household income, while *AverageIncome* is the sample mean of income. *Distance* is the individual trip distance, and the *Average-Distance* is the sample mean of distance.

Table 9
Assumptions for the non-chosen mode of transport alternatives.

Mode	Travel time (minutes)	Travel cost (thousand IDR/km)	Waiting time (minute)	Transfer	Walking time transit (minute)	β ODT	Availability
Walk	API Walking	-	-	-	-	-	always
Bike	$\frac{APICarDistance}{SpeedBike}$	-	-	-	-	-	always
Car	CarAPI	2.95	-	-	-	-	Access Car
MC	$\frac{APICarDistance}{APICarSpeed + 3km*\ h^{-1}}$	0.59	-	-	-	-	Access MC
Car ODT	API Car	$10(base) + 3.5$	5	-	-	Yes	Always
MC ODT	$\frac{APICarDistance}{APICarSpeed + 3km*\ h^{-1}}$	$10(4km) + 2.5$	5	-	-	Yes	Always
Bus	API Transit	10 per 10 km	API Transit	API Transit	API Transit	-	Has transit
BRT	API Transit	3.5	API Transit	API Transit	API Transit	-	Has transit
Train	API Transit	5.5	API Transit	API Transit	API Transit	-	Has train
Microbus (angkot)	API Car	5 per 10 km	5	> 10 km	5	-	Always
Car taxi	API Car	$6(base) + 4.5$	5	-	-	-	Always
MC taxi	$\frac{APICarDistance}{APICarSpeed + 3km*\ h^{-1}}$	$10(base) + 3$	5	-	-	-	Always



(a) Share by age group

(b) Share by income group

(c) Share on SP and RP data set

Fig. 6. Mode of transport shares of data set.

The equation for the utility of Model 1 can be seen in Appendix (A.1–A.20), the utility equation of Model 2 can be seen in Appendix (A.21–A.40), and the utility equation of Model 3 can be seen in Appendix (A.41–A.60). The Equaions A.1 to A.11, A.21 to A.31, and A.41 to A.51 are for the RP data set, while the equations A.12-A20, A.32-A.40 A.52-A.60 are for the SP data set. The σ_{SP} is the scale parameter for the SP data set.

7. Results

7.1. Model estimates for the pooled SP and RP data

The results for the three models are presented in Table 10, in which MC is the base category. Model 1 has 11 modes of transport alternatives presented: walking, bike, bus, BRT, train, car, MC, taxi, ODT, PT SP (public transport in SP data set), UAM. Model 2, which combines all public transport modes (Bus, BRT, Train, and PT SP) into a single PT, has eight choice alternatives: walk, bike, car, MC, taxi, ODT, PT, and UAM. For Models 1 and 2, we implemented MNL model. Model 3 has the same alternatives as in Model 2. For Model 3, we implemented MXL model.

The parameters of Model 1, established travel time for a specific alternative, generic travel costs for all choice alternatives, and generic congestion charging only for car, MC, taxi, and ODT modes of transport. Socio-demographic attributes, such as household income, age, gender, and education, were specific only for some alternatives. The models include the attribute of living in the urban agglomeration for UAM. Model 2 and Model 3 had similar parameters to Model 1 except for cost and PT travel time. Cost is a combination of travel cost and congestion charging, while PT travel time in Model 2 and Model 3 is a combination of all public transport alternatives.

In the case of Model 1, we found an insignificant result for the ASC of train, meaning that the train is not more or less preferred than

Table 10
A pooled SP and RP result.

Variable	Model 1		Model 2		Model 3	
Baseline: MC	Parameter	t-test	Parameter	t-test	Parameter	t-test
ASC Walk	-2.51	−23.08***	-2.57	−23.27***	-16.38	−14.23***
ASC Bike	-4.22	−13.57***	-4.24	−13.65***	-39.48	−18.52***
ASC PT	-3.50	−25.14***	-3.75	−30.5***	-21.02	−26.28***
ASC Bus	-5.05	−13.47***	-	-	-	-
ASC BRT	-4.74	−20.3***	-	-	-	-
ASC Train	-0.29	−0.9	-	-	-	-
ASC Car	-1.20	−10.64***	-1.09	−9.05***	-14.29	−2.61***
ASC Taxi	-3.94	−23.59***	-3.82	−21.21***	-25.72	−9.28***
ASC ODT	-1.43	−9.32***	-1.23	−7.64***	-10.83	−7.02***
ASC UAM	-3.54	−6.95***	-3.23	−5.7***	-22.03	−5.89***
β Travel cost [Thousand IDR]	-1.42	−12.08***	-2.08	−15.76***	-6.46	−17.15***
β Congestion charging [Thousand IDR]	-4.13	−8.46***	-	-	-	-
λ Income, cost	-0.09	−3.06***	-0.06	−2.83***	-0.13	−3.80***
λ Distance, cost	-0.83	−19.16***	-0.75	−19.13***	-0.84	−29.59***
λ Distance, $time_{UAM}$	-14.73	−5.23***	-12.3	−9.46***	-12.01	−5.18***
σ Scale parameter MC_{SP}	0.77	32.79***	0.67	31.31***	0.19	11.28***
η Walk	-	-	-	-	-10.37	−22.82***
η Bike	-	-	-	-	17.04	20.73***
η PT	-	-	-	-	-18.59	−15.97***
η Car	-	-	-	-	17.96	2.20**
η Taxi	-	-	-	-	-13.06	−5.97***
η ODT	-	-	-	-	-14.70	−9.49***
η UAM	-	-	-	-	13.75	9.03***
β Travel time Walk [minutes]	-0.36	−6.82***	-0.52	−9.11***	-2.04	−3.65***
β Travel time Bike [minutes]	-8.61	−4.55**	-9.05	−4.79***	-20.00	−3.73***
β Travel time PT [minutes]	-0.28	−1.22	-1.49	−7.17***	-8.52	−5.29***
β Travel time Bus [minutes]	-1.18	−1.4	-	-	-	-
β Travel time BRT [minutes]	-1.07	−2.36**	-	-	-	-
β Travel time Train [minutes]	-2.72	−6.39***	-	-	-	-
β Travel time Car [minutes]	-0.60	−3.64***	-1.24	−6.33***	-5.15	−3.01***
β Travel time MC [minutes]	-2.34	−10.25***	-3.32	−12.68***	-10.13	−5.88***
β Travel time Taxi [minutes]	-3.49	−8.03***	-4.79	−9.23***	-9.63	−1.73*
β Travel time ODT [minutes]	-5.10	−15.27**	-6.26	−16.82***	-15.67	−8.48**
β Travel time UAM [minutes]	-1.36	−31.83***	-2.65	−3.12***	-12.41	−2.37**
β Access time UAM	-3.54	−1.82*	-4.54	−2.02**	-15.51	−1.38
β Male ODT	-0.38	−4.87***	-0.42	−4.95***	-3.13	−1.41
β Male UAM	-0.04	−0.20	-0.05	−0.21	0.29	0.19
βAge Walking	0.99	3.69***	-0.52	−9.11***	10.41	1.05
βAge Train	-0.15	−2.01**	-	-	-	-
βAge MC	-0.93	−3.96***	-0.83	−2.45***	-2.72	−0.46
βAge ODT	-1.36	−4.05***	-1.32	−3.75***	-11.13	−0.94
βAge UAM	-3.44	−3.48***	-3.76	−3.35***	-22.91	−2.78***
βUniversity degree ODT	0.25	2.86***	0.27	2.97***	3.45	7.34***
βUniversity degree UAM	0.93	4.09***	1.08	4.17***	6.88	4.10***
βAgglomeration UAM	0.34	1.47	0.15	0.58	0.19	0.13
Observations	52731		52731		52731	
Draws	-		-		1000	
Final-LL	-57153		-59103		-33948	
Rho-square	0.44		0.42		0.67	
AIC	114381		118267		67970	
BIC	114709		118533		68299	

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

a MC. However, the other choice alternatives had negative and significant ASCs, suggesting that the MC is more preferred than the alternative choices. In Model 2 and Model 3, we found that the ASCs for all choice alternatives were negative, showing that the MC is preferred more than the other transport choice alternatives.

In the models, we found that males, non-university, and older people were less likely to choose ODT, which is supported by significance of male ODT (+), university degree ODT (+), and age ODT (-). Except in Model 3, only age for UAM is significant, and being male in ODT is not significant. For UAM, the impact of being male and living outside Jakarta (in the urban agglomeration) was not statistically significant. However, the young and university degree holding respondents tended to choose UAM. It is supported from the significant of age UAM (-), and university degree UAM (+). This finding is in line with that by Eker et al. (2020a), that young respondents tend to choose UAM. Furthermore, variable travel costs, congestion charging, and access time of UAM were negatively significant, as expected.

The variable of travel time for all choice alternatives was negative and significant in all models, and significant except for PT (in the SP data set) and bus in Model 1. These results suggests that they did not like biking. This finding may be because the bike lane facilities do not accommodate bikers very well, and bikers have to compete for space with the motorized vehicles. Furthermore, hot weather makes it difficult to ride bikes. All models also indicate that respondents like to use cars and MC, and that residents in Jakarta prefer to use private vehicles. However, for UAM, from beta travel time, we can see that in Model 1 and Model 2, the respondents immensely enjoy the UAM after Car, but Model 3 indicates that UAM is just somewhat more enjoyable than ODT.

In model 1, the travel time of PT in SP and bus were not significant. However, travel time of BRT and train were negative and significant. People preferred to use BRT rather than a train because the train was less accessible. The number of BRT stops and lines are higher than train stations and lines: 325 BRT lines and 22 commuter lines. Moreover, people still need to take other modes to go to the train station. The λ of income and distance for all models is negative and significant, as shown in Vrtic et al. (2010).

With regard to BIC and rho-square, Model 3 (MXL) outperforms the other models, and Model 2 is better than Model 1. Those models provide a better fit than previous studies of Greater Jakarta (Belgiawan et al., 2019b; Ilahi et al., 2019).

7.2. Value of travel time savings

We measured the VTTS of a person in U.S dollars (USD). VTTS measures a person's willingness to pay in return for a reduction of travel time. As our scenario was conducted using Indonesia Rupiah (IDR), we converted IDR into USD, and calculated the VTTS using the following formula:

$$\mathrm{VTTS}_{\mathrm{i,n}} = \frac{\delta \mathrm{V}_{\mathrm{i,n}} / \delta \mathrm{T}_{\mathrm{i,n}}}{\delta \mathrm{V}_{\mathrm{i,n}} / \delta \mathrm{C}_{\mathrm{i,n}}} = \frac{60,000}{14,000} * \frac{\beta \mathrm{T}}{\beta \mathrm{C}} \tag{3}$$

where $V_{i,n}$ represents systematic utility for an alternative i for person n, $T_{i,n}$ represents travel time for the person n choosing alternative i, and $C_{i,n}$ represents the cost for the person n choosing an alternative i. The parameters of time and cost are represented by βT and βC respectively.

Table 11 shows the results of the VTTS at the sample mean. It presents the willingness to reduce travel time by one unit. Public Transport in Table 11 and 12 refers to general public transport, as in the SP dataset the mode is an aggregate of all PT services. The specific modes of transport, like Bus, BRT, and Train, are from the RP dataset based on the assumptions in Table 9.

We found that the VTTS of the PT (in the SP data set) was the lowest, but the travel time parameter of PT was not significant. The VTTS of cars was lower than that of the other modes of transport. The result is the same as that of Ilahi et al. (2019); Belgiawan et al. (2019b); however, it differs from that of Schmid et al. (2019); Shires and de Jong (2009); Wardman (2004) that shows the car VTTS was higher than public transport. The VTTS of ODT was the highest, followed by taxi, train, and MC. Model 2 gave a similar result, in which ODT was the highest, followed by taxi, MC, UAM, PT, and car. In Model 3, the highest VTTS is ODT, followed by UAM, taxi, and MC. Furthermore, the interaction between income and distance to VTTS is shown in Fig. 7 for cars, MC, ODT and UAM.

In terms of VTTS vis-a-vis the Congestion Charge in Model 1, the ODT was the highest, followed by taxi, MC, and car, showing that the users of ODT and taxis were more sensitive to the charge. The income per capita in 2018 in Jakarta was 17,438 USD per year or 8.7 USD per hour for an assumed 2,000 h per year. However, we must consider that Indonesia has a high Gini ratio. A small number of people have very high incomes per capita. The hourly income per capita is lower than 8.7 USD if we exclude the highest-income people. We found that the VTTS vis-a-vis travel cost of ODT, taxi, and train (Model 1), ODT and taxi (Model 2), and ODT and UAM (Model 3) were higher than income per capita/hour. The VTTS vis-a-vis of access cost was higher than income per capita/hour in all models.

As has been discussed in several studies (Schmid et al., 2019; Jara-Díaz et al., 2008; Hössinger et al., 2020), the VTTS is the sum of the value of leisure (VOL) and VTAT. VOL represents the willingness to pay to reduce travel time to gain more utility, and VTAT is the indirect value disutility of travel time assigned to travel. VOL is calculated based on the proportion of hourly income and each country has a different value. Assuming that the VOL of Indonesians is similar to Chileans, approximately 66% of wages (Jara-Díaz et al., 2008) the resulting VOL is 5.74 USD. As shown in Table 11, VTAT is positive for public transport, bus, BRT, car, and UAM (Model 1), and public transport, car, and UAM (Model 2). However, only the car and public transport in Model 3 have a positive VTAT. The higher the VTAT, the lower the VTTS. In the meantime, the lower the VTAT, the higher the VTTS. The positive value of VTAT shows disutility when travel time is reduced; it therefore reveals more about comfort, safety, and security during travel, than the travel time itself.

Table 11
Value of time of mode of transport pool SP and RP (USD/hour).

Model	Mode	Fuel/Ticket cost	Congestion cost	Access cost	VTAT
Model 1	Public transport	0.86	-	-	4.88
	Bus	3.56	-	-	2.18
	BRT	3.23	-	-	2.51
	Train	8.21	-	-	-2.47
	Car	1.80	0.62	-	3.94
	MC	7.06	2.43	-	-1.32
	Taxi	10.52	3.62	-	-4.78
	ODT	15.38	5.29	-	-9.68
	UAM	4.98	-	10.7	0.76
Model 2	Public transport	3.07	-	-	2.67
	Car	2.55	-	-	3.19
	MC	6.85	-	-	-1.11
	Taxi	9.88	-	-	-4.14
	ODT	12.92	-	-	-7.18
	UAM	5.47	-	9.35	0.27
Model 3	Public transport	5.65	-	-	0.09
	Car	3.42	-	-	2.32
	MC	6.72	-	-	-0.94
	Taxi	6.39	-	-	-0.65
	ODT	10.39	-	-	-4.65
	UAM	8.23	-	10.29	-2.49

Table 12
Point elasticities of variables.

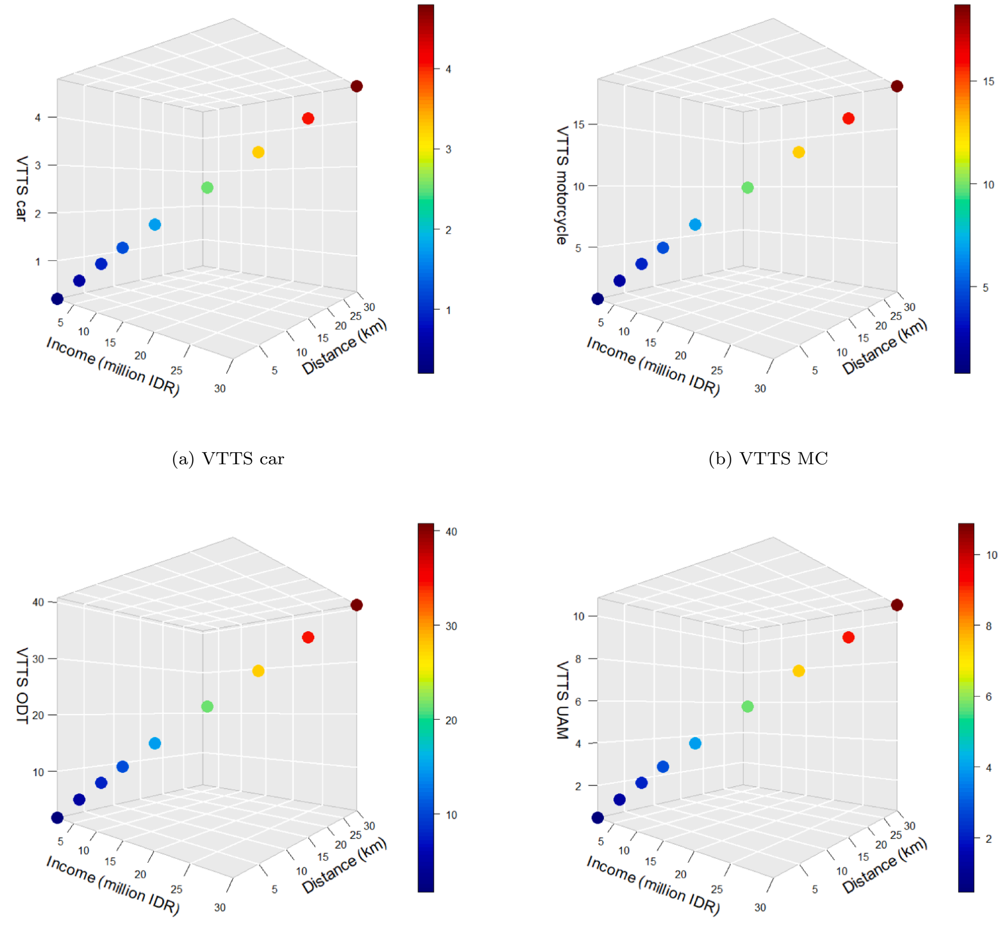
Model	Mode	Travel time	Travel cost	Congestion cost	Access time
Model 1	Walk	-0.17	-	-	-
	Bike	-0.94	-	-	-
	Bus	-0.46	-0.33	-	-
	BRT	-0.42	-0.05	-	-
	Train	-0.87	-0.05	-	-
	Car	-0.13	-0.36	-0.13	-
	MC	-0.24	-0.14	-0.05	-
	Taxi	-0.57	-0.44	-0.07	-
	ODT	-0.92	-0.43	-0.01	-
	Public transport	-0.06	−0.63	-	-
	UAM	-0.15	−2.07	-	-0.33
Model 2	Walk	-0.24	-	-	-
	Bike	-0.99	-	-	-
	Car	-0.26	-0.58	-	-
	MC	-0.34	-0.24	-	-
	Public transport	-0.54	−0.24	-	-
	Taxi	-0.75	-0.64	-	-
	ODT	-1.11	-0.68	-	-
	UAM	-0.29	−2.96	-	-0.39
Model 3	Walk	-0.95	-	-	-
	Bike	-4.26	-	-	-
	Car	-1.29	-2.15	-	-
	MC	-0.85	-0.72	-	-
	Public transport	-2.83	−0.67	-	-
	Taxi	-1.76	-2.23	-	-
	ODT	-3.39	-2.60	-	-
	UAM	-1.32	−9.55	-	-1.42

7.3. Point elasticities of travel time

In this section, we measured the direct point elasticities for all modes of travel. The method used were the same as those presented in Atasoy et al. (2013);Belgiawan et al. (2019a), as shown in Eq. 3:

$$E^{w_i}_{iqX_{kiq}} = \sum_{q=1}^{Q_s} E_{iqX_{kiq}} \frac{w_q P_{iq}}{\Sigma_{q=1}^{Q_s} w_q P_{iq}} \tag{4}$$

where w_q represents the sample weight for individual q from sample Q_s from population Q and $E_{iq}X_{kiq}$ is the disaggregate elasticity on



(a) VTTS car

(b) VTTS MC

(c) VTTS ODT

(d) VTTS UAM

Fig. 7. VTTS related to income and distance.

the demand of individual q for variations in attribute X_{kiq}. We weighted each observation in our data sets according to the representation of its age and gender category in the Greater Jakarta population.

The results are shown in Table 12. The sign of all the time and cost elasticities measurements were as expected, which means that a percentage increase in all travel time and travel cost would, on average, reduce the probability of choosing an alternative. We found that travel time for all modes was inelastic for Model 1, and ODT was elastic for Model 2. However, for Model 3, only walking and MC were inelastic. The bike had the highest reduction, in which a 1% increase in travel time would reduce the probability of choosing a bike by 4.26%, followed by ODT with a reduction of around 3.39%, and public transport of 2.83%.

Furthermore, for travel costs, only UAM was elastic for Model 1 and Model 2. However, travel cost was elastic for car, taxi, ODT, and UAM for Model 3. It showed that a 1% increase in travel cost for the UAM would reduce the probability of choosing UAM by 2.07% in Model 1, 2.96% in Model 2, and 9.55% in Model 3. In Model 3, we found that a 1% increase in travel cost would reduce the probability of choosing a car by 2.15%, a taxi by 2.23%, and ODT by 2.60%. The congestion cost was inelastic for Model 1. The access time was inelastic for Model 1 and Model 2, but was elastic for Model 3.

8. Conclusions

This paper presents a travel diary survey and its outcomes for the Greater Jakarta region. It provides the most comprehensive sample to date of the mobility behavior of people living in Greater Jakarta. This paper discusses an early effort to understand On-Demand Transport services and Urban Air Mobility (UAM) and their impacts on mobility in Greater Jakarta. We identify the patterns of trip purposes for each mode of transport and distinguish the mode choice by its socio-demographic attributes. The results indicate who made the trips, as well as when and why. We also describe the response rate and response burden. This research further enriches the scarce literature on mobility patterns in developing countries, especially considering the multitude of mode choices, some of which are informal.

Our objectives were to capture travel behavior for each mode of transportation comprehensively. The WTP for each mode was also investigated, which includes the VTTS, the VTAT, and elasticity, using pooled SP and RP data sets. The attributes of time and cost were negative and significant in all models, as expected, except for PT and the bus in Model 1. We found that the VTTS of ODT was the highest. The low VTTS of the car in our result shows that car users enjoy riding in a car. Implementing road pricing might not significantly reduce the share of cars and MC, as it was inelastic in Model 1. However, increasing PT frequency or creating a special bike lane and bus priority lane to reduce travel time could increase the shares of those modes. As can be seen in all models, we found that cars and MC are inelastic for all variables, except for cars in Model 3. This means that to reduce the share of car and MC transport by increasing their cost and time might not substantially reduce the share of those modes. In contrast, other policies may reduce the number of cars and MC, such as by creating a quota for each household for owning a private vehicle, by making it difficult for people to afford those modes, and by Implementing an odd and even license plate policy to control the number of cars in circulation.

UAM has the potential to develop, although it might be suitable only for high-income residents and long-distance travel. As seen in our results, the VTTS of UAM was relatively low. As the urban agglomeration cities in greater Jakarta are relatively far from Jakarta and the airport, UAM has an advantage compared to other choice alternatives. Moreover, severe congestion in Jakarta also provides an advantage for UAM over other alternatives. The infrastructure requirements of UAM that are needed to ensure that UAM services are adequate will take some time to cover all of Greater Jakarta. Greater Jakarta differs from cities in the U.S. such as Los Angeles and New York City, where UAM is currently available. Society still needs to be educated to become familiar with this system. Safety and security are also required to ensure that society accepts the development of this mode of transport.

In our results, ODT had the highest VTTS, suggesting that this system provide great benefits for people in Greater Jakarta. Both high and low-income people can use this transportation alternative. If a person has the app, s/he can comfortably ride the ODT service. The principal problems that still arise in the context of using ODT are related to regulation, as this system is not subject to the same regulations as other modes of travel, such as PT. MC ODT changed the behavior of conventional transaction; people do not need to negotiate the price upfront, and drivers do not need to wait for the customer at a particular place daily (called pangkalan). Regulations could be beneficial for both passengers and providers. ODT can also support the PT infrastructure. The positive value of VTAT in public transport shows that public transport's comfort, safety, and security should be considered for further improvement.

This study also reflects participation in the labor force by gender in Indonesia. Females travel more for non-work related purposes. While 81.97% of males participated in the labor force, only 50.89 % of the females are employed (Indonesia-investments, 2018). Males were more likely to work to finance household expenditures. The timing of the trip also influenced a person's choice of mode of transport. People were more likely to walk during midday instead of using MC, a car, or ODT. During the day, a trip was more likely to be for short-duration activities like eating, errands, or religious purposes. Furthermore, each mode of transport had a different speed, showing that Jakarta had lower speeds than agglomerations elsewhere.

In future studies, the travel patterns will allow us to further refine the synthetic population of Greater Jakarta (Ilahi and Axhausen, 2019) by assigning activity chains to travelers. This, together with estimated mode-choice models, will be the basis for further transport policy studies using a multi-agent transport simulation (MATSim) framework. All emerging modes available could be simulated, and a potential UAM network can be designed.

CRediT authorship contribution statement

Anugrah Ilahi: Conceptualization, Methodology, Investigation, Software, Formal analysis, Writing - Original Draft, Writing - Review & Editing. Prawira F. Belgiawan: Investigation, Formal analysis, Writing - Review & Editing. Milos Balac: Conceptualization, Methodology, Writing - Review & Editing. Kay W. Axhausen: Conceptualization, Methodology, Writing - Review & Editing, Supervision.

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Appendices

Appendix A. Utility equation of Model 1, Model 2, and Model 3

In this appendix, we present the utiliy fromulation for Model 1 (A.1 -A.20), Model 2 (A.21-A.40), Model 3 (A.41-A.60). In Model 2 and Model 3, we combine all public transport mode (bus, BRT, and train) as single public transport (PT), and travel cost (TC) and congestion charging (CC) as a single travel cost (TC).

$$U_{walk,n,t} = 1 * (\alpha_{walk} + \beta_{TT_{walk}} * TT_{walk,n,t} + \beta_{Age} * Age_n) + \epsilon_{walk,n,t} \tag{A.1}$$

$$U_{bike,n,t} = 1 * (\alpha_{bike} + \beta_{TT_{bike}} * TT_{bike,n,t}) + \epsilon_{bike,n,t} \tag{A.2}$$

$$U_{bus,n,t} = 1*(\alpha_{bus} + \beta_{TT_{bus}} * TT_{bus,n,t} + \beta_{TC} * (\frac{Distance}{AverageDistance})^{\lambda_{Distance}} * (\frac{Income}{AverageIncome})^{\lambda_{Income}} * TC_{bus,n,t}) + \epsilon_{bus,n,t} \tag{A.3}$$

$$U_{BRT,n,t} = 1*(\alpha_{BRT} + \beta_{TT_{BRT}} * TT_{BRT,n,t} + \beta_{TC} * (\frac{Distance}{AverageDistance})^{\lambda_{Distance}} * (\frac{Income}{AverageIncome})^{\lambda_{Income}} * TC_{BRT,n,t}) + \epsilon_{BRT,n,t} \tag{A.4}$$

$$U_{train,n,t} = 1*(\alpha_{train} + \beta_{TT_{train}} * TT_{train,n,t} + \beta_{TC} * (\frac{Distance}{AverageDistance})^{\lambda_{Distance}} * (\frac{Income}{AverageIncome})^{\lambda_{Income}} * TC_{train,n,t} + \beta_{Age_{train}} * Age_n) + \epsilon_{train,n,t} \tag{A.5}$$

$$U_{car,n,t} = 1*(\alpha_{car} + \beta_{TT_{car}} * TT_{car,n,t} + \beta_{TC} * (\frac{Distance}{AverageDistance})^{\lambda_{Distance}} * (\frac{Income}{AverageIncome})^{\lambda_{Income}} * TC_{car,n,t}) + \epsilon_{car,n,t} \tag{A.6}$$

$$U_{MC,n,t} = 1*(\beta_{TT_{MC}} * TT_{MC,n,t} + \beta_{TC} * (\frac{Distance}{AverageDistance})^{\lambda_{Distance}} * (\frac{Income}{AverageIncome})^{\lambda_{Income}} * TC_{MC,n,t} + \beta_{Age_{MC}} * Age_n) + \epsilon_{MC,n,t} \tag{A.7}$$

$$U_{taxi,n,t} = 1*(\alpha_{taxi} + \beta_{TT_{taxi}} * TT_{Cartaxi,n,t} + \beta_{TC} * (\frac{Distance}{AverageDistance})^{\lambda_{Distance}} * (\frac{Income}{AverageIncome})^{\lambda_{Income}} * TC_{Cartaxi,n,t}) + \epsilon_{taxi,n,t} \tag{A.8}$$

$$U_{ODT,n,t} = 1*(\alpha_{ODT} + \beta_{TT_{ODT}} * TT_{CarODT,n,t} + \beta_{TC} * (\frac{Distance}{AverageDistance})^{\lambda_{Distance}} * (\frac{Income}{AverageIncome})^{\lambda_{Income}} * TC_{CarODT,n,t} + \beta_{Male_{ODT}} * Gender_{Male,n} + \beta_{Education_{ODT}} * Education_{University,n} + \beta_{Age_{ODT}} * Age_n) + \epsilon_{ODT,n,t} \tag{A.9}$$

$$U_{taxi,n,t} = 1*(\alpha_{taxi} + \beta_{TT_{taxi}} * TT_{MCtaxi,n,t} + \beta_{TC} * (\frac{Distance}{AverageDistance})^{\lambda_{Distance}} * (\frac{Income}{AverageIncome})^{\lambda_{Income}} * TC_{MCtaxi,n,t}) + \epsilon_{taxi,n,t} \tag{A.10}$$

$$U_{ODT,n,t} = 1*(\alpha_{ODT} + \beta_{TT_{ODT}} * TT_{MCODT,n,t} + \beta_{TC} * (\frac{Distance}{AverageDistance})^{\lambda_{Distance}} * (\frac{Income}{AverageIncome})^{\lambda_{Income}} * TC_{MCODT,n,t} + \beta_{Male_{ODT}} * Gender_{Male,n} + \beta_{Education_{ODT}} * Education_{University,n} + \beta_{Age_{ODT}} * Age_n) + \epsilon_{ODT,n,t} \tag{A.11}$$

$$U_{walk_{SP},n,t} = \sigma_{SP} * (\alpha_{walk} + \beta_{TT_{walk}} * TT_{Walk_{SP},n,t} + \beta_{Age_{walk}} * Age_n) + \epsilon_{walk_{SP},n,t} \tag{A.12}$$

$$U_{PT_{SP},n,t} = \sigma_{SP} * (\alpha_{PT} + \beta_{TT_{PT}} * TT_{PT_{SP},n,t} + \beta_{TC} * (\frac{Distance}{AverageDistance})^{\lambda_{Distance}} * (\frac{Income}{AverageIncome})^{\lambda_{Income}} * TC_{PT_{SP},n,t}) + \epsilon_{PT_{SP},n,t} \tag{A.13}$$

$$\begin{aligned}U_{car_{SP},n,t} = \quad & \sigma_{SP} * (\alpha_{car} + \beta_{TT_{car}} * TT_{car_{SP,n,t}} \\ & + \beta_{TC} * (\frac{Distance}{AverageDistance})^{\lambda_{Distance}} * (\frac{Income}{AverageIncome})^{\lambda_{Income}} \\ & * TC_{car_{SP,n,t}} + \beta_{CC} * CC_{car_{SP,n,t}}) + \epsilon_{car_{SP},n,t}\end{aligned} \tag{A.14}$$

$$\begin{aligned}U_{MC_{SP},n,t} = \quad & \sigma_{SP} * (\beta_{TT_{MC}} * TT_{MC_{SP,n,t}} + \beta_{TC} \\ & * (\frac{Distance}{AverageDistance})^{\lambda_{Distance}} * (\frac{Income}{AverageIncome})^{\lambda_{Income}} \\ & * TC_{MC_{SP,n,t}} + \beta_{Age_{MC}} * Age_{MC,n} + \beta_{CC} * CC_{MC_{SP,n,t}}) + \epsilon_{MC_{SP},n,t}\end{aligned} \tag{A.15}$$

$$\begin{aligned}U_{Taxi_{SP},n,t} = \quad & \sigma_{SP} * (\alpha_{Taxi} + \beta_{TT_{Taxi}} * TT_{CarTaxi_{SP,n,t}} \\ & + \beta_{TC} * (\frac{Distance}{AverageDistance})^{\lambda_{Distance}} * (\frac{Income}{AverageIncome})^{\lambda_{Income}} \\ & * TC_{Cartaxi_{SP,n,t}} + \beta_{CC} * CC_{Cartaxi_{SP,n,t}}) + \epsilon_{Taxi_{SP},n,t}\end{aligned} \tag{A.16}$$

$$\begin{aligned}U_{ODT_{SP},n,t} = \quad & \sigma_{SP} * (\alpha_{ODT} + \beta_{TT_{ODT}} * TT_{CarODT_{SP,n,t}} + \beta_{TC} \\ & * (\frac{Distance}{AverageDistance})^{\lambda_{Distance}} * (\frac{Income}{AverageIncome})^{\lambda_{Income}} * TC_{CarODT_{SP,n,t}} \\ & + \beta_{CC} * CC_{CarODT_{SP,n,t}} + \beta_{Male_{ODT}} * Gender_{Male,n} + \beta_{Education_{ODT}} \\ & * Education_{University,n} + \beta_{Age_{ODT}} * Age_{n}) + \epsilon_{ODt_{SP},n,t}\end{aligned} \tag{A.17}$$

$$\begin{aligned}U_{Taxi_{SP},n,t} = \quad & \sigma_{SP} * (\alpha_{Taxi} + \beta_{TT_{Taxi}} * TT_{MCTaxi_{SP,n,t}} \\ & + \beta_{TC} * (\frac{Distance}{AverageDistance})^{\lambda_{Distance}} * (\frac{Income}{AverageIncome})^{\lambda_{Income}} \\ & * TC_{MCTaxi_{SP,n,t}} + \beta_{CC} * CC_{MCtaxi_{SP,n,t}}) + \epsilon_{Taxi_{SP},n,t}\end{aligned} \tag{A.18}$$

$$\begin{aligned}U_{ODT_{SP},n,t} = \quad & \sigma_{SP} * (\alpha_{ODT} + \beta_{TT_{ODT}} * TT_{MCODT_{SP,n,t}} + \beta_{TC} \\ & * (\frac{Distance}{AverageDistance})^{\lambda_{Distance}} * (\frac{Income}{AverageIncome})^{\lambda_{Income}} * TC_{MCODT_{SP,n,t}} \\ & + \beta_{CC} * CC_{MCODT_{SP,n,t}} + \beta_{Male_{ODT}} * Gender_{Male,n} + \beta_{Education_{ODT}} \\ & * Education_{University,n} + \beta_{Age_{ODT}} * Age_{n}) + \epsilon_{ODT_{SP},n,t}\end{aligned} \tag{A.19}$$

$$\begin{aligned}U_{UAM_{SP},n,t} = \quad & \sigma_{SP} * (\alpha_{UAM} + \beta_{TT_{UAM}} * (\frac{Distance}{AverageDistance})^{\lambda_{Distance}} TT_{UAM_{SP,n,t}} \\ & + \beta_{AT_{UAM}} * AT_{UAM_{SP,n,t}} + \beta_{TC} * (\frac{Distance}{AverageDistance})^{\lambda_{Distance}} \\ & * (\frac{Income}{AverageIncome})^{\lambda_{Income}} * TC_{UAM_{SP,n,t}} + \beta_{Male_{UAM}} * Gender_{Male,n} \\ & + \beta_{Location_{UAM}} * Location_{Agglomeration,n} + \beta_{Education_{UAM}} \\ & * Education_{University,n}) + \epsilon_{MC_{UAM},n,t}\end{aligned} \tag{A.20}$$

$$U_{walk,n,t} = 1 * (\alpha_{walk} + \beta_{TT_{walk}} * TT_{walk,n,t} + \beta_{Age} * Age_{n}) + \epsilon_{walk,n,t} \tag{A.21}$$

$$U_{bike,n,t} = 1 * (\alpha_{bike} + \beta_{TT_{bike}} * TT_{bike,n,t}) + \epsilon_{bike,n,t} \tag{A.22}$$

$$\begin{aligned}U_{PT,n,t} = \quad & 1 * (\alpha_{PT} + \beta_{TT_{bus}} * TT_{bus,n,t} + \beta_{TC} * (\frac{Distance}{AverageDistance})^{\lambda_{Distance}} \\ & * (\frac{Income}{AverageIncome})^{\lambda_{Income}} * TC_{PT,n,t}) + \epsilon_{PT,n,t}\end{aligned} \tag{A.23}$$

$$\begin{aligned}U_{PT,n,t} = \quad & 1 * (\alpha_{PT} + \beta_{TT_{PT}} * TT_{BRT,n,t} + \beta_{TC} * (\frac{Distance}{AverageDistance})^{\lambda_{Distance}} \\ & * (\frac{Income}{AverageIncome})^{\lambda_{Income}} * TC_{BRT,n,t}) + \epsilon_{PT,n,t}\end{aligned} \tag{A.24}$$

$$\begin{aligned} U_{PT,n,t} = \quad & 1 * (\alpha_{PT} + \beta_{TT_{PT}} * TT_{train,n,t} + \beta_{TC} * (\frac{Distance}{AverageDistance})^{\lambda_{Distance}} \\ & *(\frac{Income}{AverageIncome})^{\lambda_{Income}} * TC_{train,n,t} + \beta_{Age_{train}} * Age_n) + \epsilon_{PT,n,t} \end{aligned} \tag{A.25}$$

$$\begin{aligned} U_{car,n,t} = \quad & 1 * (\alpha_{car} + \beta_{TT_{car}} * TT_{car,n,t} + \beta_{Car} * (\frac{Distance}{AverageDistance})^{\lambda_{Distance}} \\ & *(\frac{Income}{AverageIncome})^{\lambda_{Income}} * TC_{car,n,t}) + \epsilon_{car,n,t} \end{aligned} \tag{A.26}$$

$$\begin{aligned} U_{MC,n,t} = \quad & 1 * (\beta_{TT_{MC}} * TT_{MC,n,t} + \beta_{TC} * (\frac{Distance}{AverageDistance})^{\lambda_{Distance}} \\ & *(\frac{Income}{AverageIncome})^{\lambda_{Income}} * TC_{MC,n,t} + \beta_{Age_{MC}} * Age_n) + \epsilon_{MC,n,t} \end{aligned} \tag{A.27}$$

$$\begin{aligned} U_{taxi,n,t} = \quad & 1 * (\alpha_{taxi} + \beta_{TT_{taxi}} * TT_{Cartaxi,n,t} + \beta_{TC} * (\frac{Distance}{AverageDistance})^{\lambda_{Distance}} \\ & *(\frac{Income}{AverageIncome})^{\lambda_{Income}} * TC_{Cartaxi,n,t}) + \epsilon_{taxi,n,t} \end{aligned} \tag{A.28}$$

$$\begin{aligned} U_{ODT,n,t} = \quad & 1 * (\alpha_{ODT} + \beta_{TT_{ODT}} * TT_{CarODT,n,t} + \beta_{TC} \\ & *(\frac{Distance}{AverageDistance})^{\lambda_{Distance}} * (\frac{Income}{AverageIncome})^{\lambda_{Income}} * TC_{CarODT,n,t} \\ & +\beta_{Male_{ODT}} * Gender_{Male,n} + \beta_{Education_{ODT}} * Education_{University,n} \\ & +\beta_{Age_{ODT}} * Age_n) + \epsilon_{ODT,n,t} \end{aligned} \tag{A.29}$$

$$\begin{aligned} U_{taxi,n,t} = \quad & 1 * (\alpha_{taxi} + \beta_{TT_{taxi}} * TT_{MCtaxi,n,t} + \beta_{TC} * (\frac{Distance}{AverageDistance})^{\lambda_{Distance}} \\ & *(\frac{Income}{AverageIncome})^{\lambda_{Income}} * TC_{MCtaxi,n,t}) + \epsilon_{taxi,n,t} \end{aligned} \tag{A.30}$$

$$\begin{aligned} U_{ODT,n,t} = \quad & 1 * (\alpha_{ODT} + \beta_{TT_{ODT}} * TT_{MCODT,n,t} + \beta_{TC} \\ & *(\frac{Distance}{AverageDistance})^{\lambda_{Distance}} * (\frac{Income}{AverageIncome})^{\lambda_{Income}} * TC_{MCODT,n,t} \\ & +\beta_{Male_{ODT}} * Gender_{Male,n} + \beta_{Education_{ODT}} * Education_{University,n} \\ & +\beta_{Age_{ODT}} * Age_n) + \epsilon_{ODT,n,t} \end{aligned} \tag{A.31}$$

$$U_{walk_{SP},n,t} = \sigma_{SP} * (\alpha_{walk} + \beta_{TT_{walk}} * TT_{Walk_{SP,n,t}} + \beta_{Age_{walk}} * Age_n) + \epsilon_{walk_{SP},n,t} \tag{A.32}$$

$$\begin{aligned} U_{PT_{SP},n,t} = \quad & \sigma_{SP} * (\alpha_{PT} + \beta_{TT_{PT}} * TT_{PT_{SP,n,t}} \\ & +\beta_{TC} * (\frac{Distance}{AverageDistance})^{\lambda_{Distance}} * (\frac{Income}{AverageIncome})^{\lambda_{Income}} \\ & *TC_{PT_{SP,n,t}}) + \epsilon_{PT_{SP},n,t} \end{aligned} \tag{A.33}$$

$$\begin{aligned} U_{car_{SP},n,t} = \quad & \sigma_{SP} * (\alpha_{car} + \beta_{TT_{car}} * TT_{car_{SP,n,t}} \\ & +\beta_{TC} * (\frac{Distance}{AverageDistance})^{\lambda_{Distance}} * (\frac{Income}{AverageIncome})^{\lambda_{Income}} \\ & *TC_{car_{SP,n,t}} + \beta_{CC} * CC_{car_{SP,n,t}}) + \epsilon_{car_{SP},n,t} \end{aligned} \tag{A.34}$$

$$\begin{aligned} U_{MC_{SP},n,t} = \quad & \sigma_{SP} * (\beta_{TT_{MC}} * TT_{MC_{SP,n,t}} + \beta_{TC} \\ & *(\frac{Distance}{AverageDistance})^{\lambda_{Distance}} * (\frac{Income}{AverageIncome})^{\lambda_{Income}} \\ & *TC_{MC_{SP,n,t}} + \beta_{Age_{MC}} * Age_{MC,n} + \beta_{CC} * CC_{MC_{SP,n,t}}) + \epsilon_{MC_{SP},n,t} \end{aligned} \tag{A.35}$$

$$\begin{aligned} U_{Taxi_{SP},n,t} = \quad & \sigma_{SP} * (\alpha_{Taxi} + \beta_{TT_{Taxi}} * TT_{CarTaxi_{SP,n,t}} \\ & +\beta_{TC} * (\frac{Distance}{AverageDistance})^{\lambda_{Distance}} * (\frac{Income}{AverageIncome})^{\lambda_{Income}} \\ & *(TC_{Cartaxi_{SP,n,t}} + CC_{Cartaxi_{SP,n,t}})) + \epsilon_{Taxi_{SP},n,t} \end{aligned} \tag{A.36}$$

$$\begin{aligned} U_{ODT_{SP},n,t} = \quad & \sigma_{SP} * (\alpha_{ODT} + \beta_{TT_{ODT}} * TT_{CarODT_{SP,n,t}} + \beta_{TC} \\ & *(\frac{Distance}{AverageDistance})^{\lambda_{Distance}} * (\frac{Income}{AverageIncome})^{\lambda_{Income}} \\ & *(TC_{CarODT_{SP,n,t}} + CC_{CarODT_{SP,n,t}}) + \beta_{Male_{ODT}} * Gender_{Male,n} \\ & +\beta_{Education_{ODT}} * Education_{University,n} + \beta_{Age_{ODT}} * Age_n) + \epsilon_{ODt_{SP},n,t} \end{aligned} \tag{A.37}$$

$$\begin{aligned} U_{Taxi_{SP},n,t} = \quad & \sigma_{SP} * (\alpha_{Taxi} + \beta_{TT_{Taxi}} * TT_{MCTaxi_{SP,n,t}} \\ & +\beta_{TC} * (\frac{Distance}{AverageDistance})^{\lambda_{Distance}} * (\frac{Income}{AverageIncome})^{\lambda_{Income}} \\ & *(TC_{MCTaxi_{SP,n,t}} + CC_{MCtaxi_{SP,n,t}})) + \epsilon_{Taxi_{SP},n,t} \end{aligned} \tag{A.38}$$

$$\begin{aligned} U_{ODT_{SP},n,t} = \quad & \sigma_{SP} * (\alpha_{ODT} + \beta_{TT_{ODT}} * TT_{MCODT_{SP,n,t}} + \beta_{TC} \\ & *(\frac{Distance}{AverageDistance})^{\lambda_{Distance}} * (\frac{Income}{AverageIncome})^{\lambda_{Income}} \\ & *(TC_{MCODT_{SP,n,t}} + CC_{MCODT_{SP,n,t}}) + \beta_{Male_{ODT}} * Gender_{Male,n} \\ & +\beta_{Education_{ODT}} * Education_{University,n} + \beta_{Age_{ODT}} * Age_n) + \epsilon_{ODT_{SP},n,t} \end{aligned} \tag{A.39}$$

$$\begin{aligned} U_{UAM_{SP},n,t} = \quad & \sigma_{SP} * (\alpha_{UAM} + \beta_{TT_{UAM}} * (\frac{Distance}{AverageDistance})^{\lambda_{Distance}} TT_{UAM_{SP,n,t}} \\ & +\beta_{AT_{UAM}} * AT_{UAM_{SP,n,t}} + \beta_{TC} * (\frac{Distance}{AverageDistance})^{\lambda_{Distance}} \\ & *(\frac{Income}{AverageIncome})^{\lambda_{Income}} * TC_{UAM_{SP,n,t}} + \beta_{Male_{UAM}} * Gender_{Male,n} \\ & +\beta_{Location_{UAM}} * Location_{Agglomeration,n} + \beta_{Education_{UAM}} \\ & *Education_{University,n}) + \epsilon_{MC_{UAM},n,t} \end{aligned} \tag{A.40}$$

$$U_{walk,n,t} = 1 * (\alpha_{walkRND} + \beta_{TT_{walk}} * TT_{walk,n,t} + \beta_{Age} * Age_n) + \epsilon_{walk,n,t} \tag{A.41}$$

$$U_{bike,n,t} = 1 * (\alpha_{bikeRND} + \beta_{TT_{bike}} * TT_{bike,n,t}) + \epsilon_{bike,n,t} \tag{A.42}$$

$$\begin{aligned} U_{PT,n,t} = \quad & 1 * (\alpha_{PTRND} + \beta_{TT_{bus}} * TT_{bus,n,t} + \beta_{TC} * (\frac{Distance}{AverageDistance})^{\lambda_{Distance}} \\ & *(\frac{Income}{AverageIncome})^{\lambda_{Income}} * TC_{PT,n,t}) + \epsilon_{PT,n,t} \end{aligned} \tag{A.43}$$

$$\begin{aligned} U_{PT,n,t} = \quad & 1 * (\alpha_{PTRND} + \beta_{TT_{PT}} * TT_{BRT,n,t} + \beta_{TC} * (\frac{Distance}{AverageDistance})^{\lambda_{Distance}} \\ & *(\frac{Income}{AverageIncome})^{\lambda_{Income}} * TC_{BRT,n,t}) + \epsilon_{PT,n,t} \end{aligned} \tag{A.44}$$

$$\begin{aligned} U_{PT,n,t} = \quad & 1 * (\alpha_{PTRND} + \beta_{TT_{PT}} * TT_{train,n,t} + \beta_{TC} * (\frac{Distance}{AverageDistance})^{\lambda_{Distance}} \\ & *(\frac{Income}{AverageIncome})^{\lambda_{Income}} * TC_{train,n,t} + \beta_{Age_{train}} * Age_n) + \epsilon_{PT,n,t} \end{aligned} \tag{A.45}$$

$$\begin{aligned} U_{car,n,t} = \quad & 1 * (\alpha_{carRND} + \beta_{TT_{car}} * TT_{car,n,t} + \beta_{Car} * (\frac{Distance}{AverageDistance})^{\lambda_{Distance}} \\ & *(\frac{Income}{AverageIncome})^{\lambda_{Income}} * TC_{car,n,t}) + \epsilon_{car,n,t} \end{aligned} \tag{A.46}$$

$$\begin{aligned} U_{MC,n,t} = \quad & 1*(\beta_{TT_{MC}}*TT_{MC,n,t}+\beta_{TC}*(\frac{Distance}{AverageDistance})^{\lambda_{Distance}} \\ & *(\frac{Income}{AverageIncome})^{\lambda_{Income}}*TC_{MC,n,t}+\beta_{Age_{MC}}*Age_n)+\epsilon_{MC,n,t} \end{aligned} \tag{A.47}$$

$$\begin{aligned} U_{taxi,n,t} = \quad & 1*(\alpha_{taxiRND}+\beta_{TT_{taxi}}*TT_{Cartaxi,n,t}+\beta_{TC}*(\frac{Distance}{AverageDistance})^{\lambda_{Distance}} \\ & *(\frac{Income}{AverageIncome})^{\lambda_{Income}}*TC_{Cartaxi,n,t})+\epsilon_{taxi,n,t} \end{aligned} \tag{A.48}$$

$$\begin{aligned} U_{ODT,n,t} = \quad & 1*(\alpha_{ODTRND}+\beta_{TT_{ODT}}*TT_{CarODT,n,t}+\beta_{TC} \\ & *(\frac{Distance}{AverageDistance})^{\lambda_{Distance}}*(\frac{Income}{AverageIncome})^{\lambda_{Income}}*TC_{CarODT,n,t} \\ & +\beta_{Male_{ODT}}*Gender_{Male,n}+\beta_{Education_{ODT}}*Education_{University,n} \\ & +\beta_{Age_{ODT}}*Age_n)+\epsilon_{ODT,n,t} \end{aligned} \tag{A.49}$$

$$\begin{aligned} U_{taxi,n,t} = \quad & 1*(\alpha_{taxiRND}+\beta_{TT_{taxi}}*TT_{MCtaxi,n,t}+\beta_{TC}*(\frac{Distance}{AverageDistance})^{\lambda_{Distance}} \\ & *(\frac{Income}{AverageIncome})^{\lambda_{Income}}*TC_{MCtaxi,n,t})+\epsilon_{taxi,n,t} \end{aligned} \tag{A.50}$$

$$\begin{aligned} U_{ODT,n,t} = \quad & 1*(\alpha_{ODTRND}+\beta_{TT_{ODT}}*TT_{MCODT,n,t}+\beta_{TC} \\ & *(\frac{Distance}{AverageDistance})^{\lambda_{Distance}}*(\frac{Income}{AverageIncome})^{\lambda_{Income}}*TC_{MCODT,n,t} \\ & +\beta_{Male_{ODT}}*Gender_{Male,n}+\beta_{Education_{ODT}}*Education_{University,n} \\ & +\beta_{Age_{ODT}}*Age_n)+\epsilon_{ODT,n,t} \end{aligned} \tag{A.51}$$

$$U_{walk_{SP},n,t}=\sigma_{SP}*(\alpha_{walkRND}+\beta_{TT_{walk}}*TT_{Walk_{SP,n,t}}+\beta_{Age_{walk}}*Age_n)+\epsilon_{walk_{SP},n,t} \tag{A.52}$$

$$\begin{aligned} U_{PT_{SP},n,t} = \quad & \sigma_{SP}*(\alpha_{PTRND}+\beta_{TT_{PT}}*TT_{PT_{SP,n,t}} \\ & +\beta_{TC}*(\frac{Distance}{AverageDistance})^{\lambda_{Distance}}*(\frac{Income}{AverageIncome})^{\lambda_{Income}} \\ & *TC_{PT_{SP,n,t}})+\epsilon_{PT_{SP},n,t} \end{aligned} \tag{A.53}$$

$$\begin{aligned} U_{car_{SP},n,t} = \quad & \sigma_{SP}*(\alpha_{carRND}+\beta_{TT_{car}}*TT_{car_{SP,n,t}} \\ & +\beta_{TC}*(\frac{Distance}{AverageDistance})^{\lambda_{Distance}}*(\frac{Income}{AverageIncome})^{\lambda_{Income}} \\ & *TC_{car_{SP,n,t}}+\beta_{CC}*CC_{car_{SP,n,t}})+\epsilon_{car_{SP},n,t} \end{aligned} \tag{A.54}$$

$$\begin{aligned} U_{MC_{SP},n,t} = \quad & \sigma_{SP}*(\beta_{TT_{MC}}*TT_{MC_{SP,n,t}}+\beta_{TC} \\ & *(\frac{Distance}{AverageDistance})^{\lambda_{Distance}}*(\frac{Income}{AverageIncome})^{\lambda_{Income}} \\ & *TC_{MC_{SP,n,t}}+\beta_{Age_{MC}}*Age_{MC,n}+\beta_{CC}*CC_{MC_{SP,n,t}})+\epsilon_{MC_{SP},n,t} \end{aligned} \tag{A.55}$$

$$\begin{aligned} U_{Taxi_{SP},n,t} = \quad & \sigma_{SP}*(\alpha_{TaxiRND}+\beta_{TT_{Taxi}}*TT_{CarTaxi_{SP,n,t}} \\ & +\beta_{TC}*(\frac{Distance}{AverageDistance})^{\lambda_{Distance}}*(\frac{Income}{AverageIncome})^{\lambda_{Income}} \\ & *(TC_{Cartaxi_{SP,n,t}}+CC_{Cartaxi_{SP,n,t}}))+\epsilon_{Taxi_{SP},n,t} \end{aligned} \tag{A.56}$$

$$\begin{aligned} U_{ODT_{SP},n,t} = \quad & \sigma_{SP}*(\alpha_{ODTRND}+\beta_{TT_{ODT}}*TT_{CarODT_{SP,n,t}}+\beta_{TC} \\ & *(\frac{Distance}{AverageDistance})^{\lambda_{Distance}}*(\frac{Income}{AverageIncome})^{\lambda_{Income}} \\ & *(TC_{CarODT_{SP,n,t}}+CC_{CarODT_{SP,n,t}})+\beta_{Male_{ODT}}*Gender_{Male,n} \\ & +\beta_{Education_{ODT}}*Education_{University,n}+\beta_{Age_{ODT}}*Age_n)+\epsilon_{ODt_{SP},n,t} \end{aligned} \tag{A.57}$$

$$\begin{aligned} U_{Taxi_{SP},n,t} = \; & \sigma_{SP} * (\alpha_{TaxiRND} + \beta_{TT_{Taxi}} * TT_{MCTaxi_{SP,n,t}} \\ & + \beta_{TC} * (\frac{Distance}{AverageDistance})^{\lambda_{Distance}} * (\frac{Income}{AverageIncome})^{\lambda_{Income}} \\ & * (TC_{MCTaxi_{SP,n,t}} + CC_{MCtaxi_{SP,n,t}})) + \epsilon_{Taxi_{SP},n,t} \end{aligned} \tag{A.58}$$

$$\begin{aligned} U_{ODT_{SP},n,t} = \; & \sigma_{SP} * (\alpha_{ODTRND} + \beta_{TT_{ODT}} * TT_{MCODT_{SP,n,t}} + \beta_{TC} \\ & * (\frac{Distance}{AverageDistance})^{\lambda_{Distance}} * (\frac{Income}{AverageIncome})^{\lambda_{Income}} \\ & * (TC_{MCODT_{SP,n,t}} + CC_{MCODT_{SP,n,t}}) + \beta_{Male_{ODT}} * Gender_{Male,n} \\ & + \beta_{Education_{ODT}} * Education_{University,n} + \beta_{Age_{ODT}} * Age_n) + \epsilon_{ODT_{SP},n,t} \end{aligned} \tag{A.59}$$

$$\begin{aligned} U_{UAM_{SP},n,t} = \; & \sigma_{SP} * (\alpha_{UAMRND} + \beta_{TT_{UAM}} * (\frac{Distance}{AverageDistance})^{\lambda_{Distance}} TT_{UAM_{SP,n,t}} \\ & + \beta_{AT_{UAM}} * AT_{UAM_{SP,n,t}} + \beta_{TC} * (\frac{Distance}{AverageDistance})^{\lambda_{Distance}} \\ & * (\frac{Income}{AverageIncome})^{\lambda_{Income}} * TC_{UAM_{SP,n,t}} + \beta_{Male_{UAM}} * Gender_{Male,n} \\ & + \beta_{Location_{UAM}} * Location_{Agglomeration,n} + \beta_{Education_{UAM}} \\ & * Education_{University,n}) + \epsilon_{MC_{UAM},n,t} \end{aligned} \tag{A.60}$$

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