THE INFLUENCE OF PARKING CHARGE DIFFERENTIATION ON THE PARKING LOCATION CHOICE IN THE CITY CENTRE OF YOGYAKARTA

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Abstract: This paper demonstrates the effect of parking charge differentiation on the parking location choice in the city centre of Yogyakarta, Indonesia. The research concentrates on how car drivers who make shopping trips would respond to the change of parking charge. This was formulated as a choice problem by utilizing heteroscedastic extreme value (HEV) model. It allows difference variances across alternatives. The research was taking place in the main shopping area, known as Malioboro, in Yogyakarta. The parking location choices would be either parking at the closest place to the shopping activities (up to 100 m), parking at the medium distance (100-300 m), or parking at the fringe of the study area (300-500 m). Due to the need for a big data set to estimate the HEV model, the model is kept very simple taking into account parking charge as the only explanatory variables in the utility function. The model predicts that 1% increase of parking charge at the core would result in the reduction of choice probability at the core area by 0.846 %, and increasing the choice probability of the medium distance locations and the fringe locations by 1.238 % and 0.853 % respectively. The model can then be used as a tool in traffic management policies in the city centre of Yogyakarta.

Keywords: parking choice, price differentiation, heteroscedastic extreme value model, Indonesia

1. INTRODUCTION

Urban transport problems in Asian big cities have come to the severe conditions (see for example: Midgley, 1994; The World Bank Report, 1986). It does happen in Indonesian big cities too (Budiono, 1999). This was caused by factors, such as: inefficient use of private cars, not well-regulated public transport operation, inefficient use of parking space, the use of limited space by street vendors. The World Bank (1986) encourages the application of congestion and pollution charges, a better public transport operation and management, and private transport demand management. It should be born in mind, however, that no single solution can solve urban transport problems.

The study area, known as Malioboro, is the main shopping area in Yogyakarta. The area is divided into blocks by grid type of roads (see Figure 1). At present, car drivers may park their cars in every place in the area. They may be either on-street or off-street parking spaces. Off-street parking is provided on the basis of fixed rate without time limit. This means that every car may park for hours without additional charges. Several on-street parking which mainly owned by the shop owners ask for additional charge if a car parks more than two hours. During shopping peak hours this area is heavily congested since most of the shoppers want to park their vehicles as close to the shopping destination as possible. Recent survey conducted by STA (2000) indicates that 84% of the respondents (out of 2500 sample) feels that Malioboro area is no more attractive and convenience due to traffic and parking problems. There has been no attempt from the Municipality to establish parking policies so as to distribute, spatially or temporally, the parking vehicles.

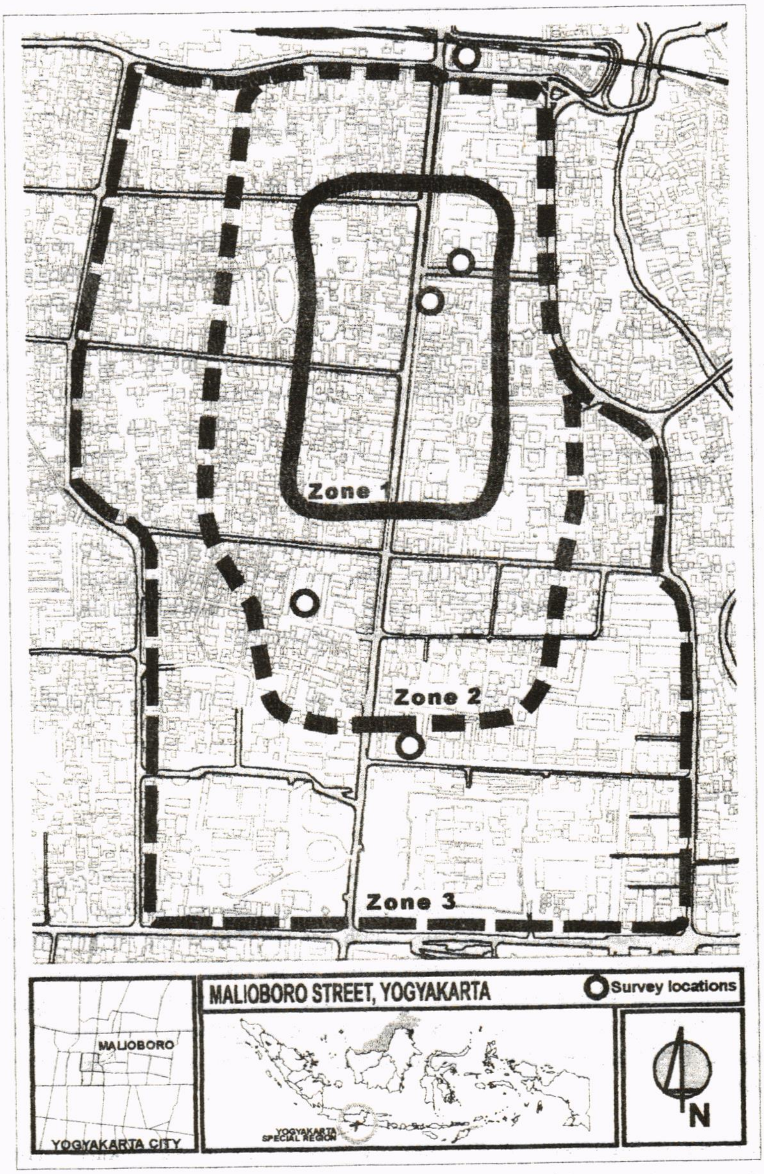

Figure 1. Study Area and Survey Locations

Traffic restraint is one of the traffic management strategies to reduce the transport demand entering city centre. This strategy is to reduce congestion and increase the environment quality. Parking charge differentiation in the city centre is one of the traffic management techniques that can be applied to change the traffic behaviour. A higher parking charge in the city centre will theoretically shift the parking location choice. Parking location choice is influenced by, among others, parking charge, walking distance, and walking convenience. The paper will demonstrate the impact of parking charge differentiation on the probability of parking choice in the city centre. The paper aims at evaluating how car users will respond to the parking charge differentiation strategy in the city of Yogyakarta, Indonesia.

2. FORMULATING PARKING LOCATION AS A CHOICE PROBLEM

Theoretically, car drivers will park their cars in the city center as close as possible to their destinations. They will choose another parking places if the parking fee in the closest place is considered to be too high. However, parking cost doesn't seem to be the only factors determining the parking location choice. Lambe (1996) formulated that the parking choice was influenced by the parking fee, the driving distance from the origin to the parking place and the walking distance from the parking place to the destination. Hensher and King (2001), using stated preference method, introduced parking hours of operation, parking charges, and walking time as the explanatory variables in the utility function. Apart from car park and driver attributes, Thompson et.al. (2001) invokes the influence of parking guidance and information system in their parking location choice model.

Parking location problems may be described as a choice problem, which can be based on the discrete choice theory explaining the individual choice for some competing options. A choice from a choice set containing two or more alternatives requires a decision rule (Ben-Akiva and Lerman, 1994). The rules can be classified into four categories: dominance, satisfaction, lexicographic, and utility. The utility rule based on economic rationality was widely adopted in transport choice problems. This class of decision rules assumed commensurability of attributes. This defined a single objective function expressing the attraction of an alternative in terms of its attributes. This index of attractiveness is known as *utility*, a measure that a decision-maker attempts to maximize through his or her choice (Ben-Akiva and Lerman, 1994). Train (1986) stated that representative utility has been assumed to be linear. This assumption is maintained in the great majority of applications. Since, under fairly general conditions, any parametric function can be approximated arbitrarily closely by a function that is linear in parameters, this assumption does not necessarily introduce significant errors.

A decision-maker is considered to choose alternative that produce the maximum utility or attractiveness. Utility could not be measured directly and, therefore, should be considered as random. As a consequence, utility is modeled as random. This means that the model will only provide the probability of the choice. The probability will be a function of factors that are believed to influence that behavior, and will usually invoke unknown parameters. This understanding cause an introduction of random term which represents the difference among decision-makers, i.e.:

$$U_{ji} = \Sigma\beta_j . x_j + \varepsilon_{ji}, \forall \text{ i. J} \quad \text{.......(1)}$$

where,

U_{ji}: total utility from alternative j of individual i

($\Sigma\beta_j . x_j$): systematic or fixed utility from alternative j, by individual i (V_{ji}), x_j is travel attributes

ε_{ji}: random utility

This formulae cause probability in the choice depending not only on Uj values but also on the influence of characteristics of random ε_{ji}, i.e: characteristics joint probability density function $\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_j$.. If ε is independent and Weibully distributed, the model will be known as logit model, while assuming ε as normally distributed will lead to probit model, and if ε is assumed to be type 1 extreme value distributed, the model is known as heteroscedastic extreme value (HEV) model.

Each attribute in the indirect utility expression associated with an alternative has a beta (β) parameter to reflect its contribution to variation in the level of relative utility, which is the product of two components – a location or scale parameter and a taste weight parameter (Hensher and Louviere, 1998). In the simple logit form with constant variance in the unobserved effects, it is well known that the scale parameter is an index of variability in the unobserved effects, which can be set equal to one arbitrarily. The simple MNL form assumes that this constant scalar is independent of the alternatives in a choice set; hence it does not affect comparisons of values across alternatives (McFadden in Hensher and Louviere, 1998). The advantage of the logit model is a result of restrictive assumption that the distributions of the random components of the stochastic utility functions are independent of each other. This assumption leads to the 'independent of irrelevant alternatives' (IIA) axiom. The use of nested logit models may overcome the IIA restriction. However, it requires a-priori specification of homogeneous sets of alternatives for which the IIA applies. In other words, a relevant subset must be defined before the model is estimated (Allenby and Ginter, 1995).

Logit model has been adopted by Thompson et.al (2001) to formulate their parking location choice model, while Lambe (1996) conducted the parking location choice estimation using probit and logit models. On the other hand, Hensher and King (2001) used nested logit model by selectively allowing differential variances between subsets of alternatives while preserving the constant variance assumption amongst other alternatives. HEV model has not been used for parking choice modelling. The application of HEV model, as can be found in, for example: Allenby and Ginter (1995), Baltas and Doyle (1998), Bhat (1995). Louviere et.al. (in press, Draft), provides methods to relax the constant variance assumption. HEV model overcomes IIA restriction and offers a more intuitive and flexible approach to modelling consumers choice. However, the estimation is often impossible without extensive data sets to permit isolation of all the possible sources of differences in random components (Hensher and King, 2001).

The Heteroscedastic Extreme Value (HEV) model completely relax the assumption of *identically distributed* random components. The HEV model provides the vehicle for *free variance* (up to identification) for all alternatives in a choice set (Louviere, et.al., in press- Draft). A nested logit model with a unique inclusive value parameter for each alternative (with one arbitrarily chosen variance equal to 1.0 for identification) is equivalent to an HEV specification. The model specification and described below refers to Louviere et al (in press, Draft).

The probability density function f (.) and the cumulative distribution function F (.) of the standard type 1 extreme value distribution associated with the random error term for the ith alternative with unrestricted variances and scale parameter λ_i are given as:

$$f(\varepsilon_i) = \frac{1}{\lambda_i} e^{\frac{t_i}{\lambda_i}} e^{-e^{\frac{\varepsilon_i}{\lambda_i}}} \quad \ldots\ldots (2)$$

$$F_i(z) = \int_{\varepsilon=-\infty}^{\varepsilon=z} f(\varepsilon_i) d\varepsilon_i = e^{-e^{\frac{z}{\lambda_i}}}$$

λ_i is the inverse of the standard deviation of the random component; hence its presence with the subscript *i* indicates that the variances can be different for each alternative in a choice set. The probability that an individual will choose alternative i (P_i) from the set C of available alternatives, given the probability distribution for the random components and non-independence among the random components, is summarized below

$$P_i = \text{Prob}\left(U_i > \text{U}_j\right), \text{for all j} \neq \text{i, j} \in \text{C}$$
$$= \text{Prob}\left(\varepsilon_j \leq \text{V}_i - \text{V}_j + \varepsilon_i\right), \text{for all j} \neq \text{i, j} \in \text{C}$$
$$= \int_{\varepsilon_i=-\infty}^{\varepsilon_i=+\infty} \prod_{j \in C, j \neq i} F\left[\frac{V_i - V_j + \varepsilon_i}{\lambda_j}\right] \frac{1}{\lambda_i} f\left(\frac{\varepsilon_i}{\lambda_i}\right) d\varepsilon_i \quad \text{.......... (4)}$$

Substituting $z = \varepsilon_i / \lambda_i$, the probability of choosing alternative ***i*** can be rewritten, as follows.

$$P_i = \int_{z=-\infty}^{z=+\infty} \prod_{j \in C, j \neq i} F\left[\frac{V_i - V_j + \lambda_{i^z}}{\lambda_j}\right] f(z)\, dz \quad \text{.......... (5)}$$

The probabilities given by the above expression sum to one over all alternatives. If the scale parameters of the random components of all alternatives are equal, then the probability expression collapses to the MNL.

The HEV model avoids the pitfalls of the IID property by allowing different scale parameters across alternatives. The scale parameter of the error term, therefore, represents the level of uncertainty (the lower the scale, the higher the uncertainty). It sets the relative weights of the observed and unobserved components in estimating the choice probability. To estimate the HEV model, the method of full information maximum likelihood is appropriate (see Louviere et.al, in press, for details). The parameters to be estimated are the utility parameter vector β and the scale parameters of the random component of each of the alternatives (one of the scale parameters is normalized to one for identifiability).

3. THE SURVEY

3.1 Survey method

In this study, the area is divided into three zones (see Figure 1) where zone 1 is the closest zone to various shopping stores, while zone 3 is the most far from the zone 1. The average walking distance in zone 1 is less than 100 m, while the average walking distance in zone 2 to the main shopping center is approximately 100-300 m. Moreover, the average walking distance for those who parks their cars in zone 3 is about 300-500 m. Shops are distributed across the area. However, zone 1 would be the area where most people do the shopping. The survey was taking place in the period of May – June 2000 in several locations as indicated in the Figure 1. The survey hours were chosen during off peak shopping hours so that the drivers can really choose their parking places. The survey was a direct face-to-face interview where selected respondents were asked to respond to the questionnaire. Since the interviews took place at parking areas, they should not be too long and the question was prepared to be quite simple and easy to understand (see Table 1).

Stated preference (SP) approaches allow analysts greater flexibility in their study of choice situations outside existing conditions. It is a method where real-life controlled experiments within the transport system can be undertaken (Ortuzar and Willumsen, 1994). The questionnaire design is somewhat inefficient since it was not systematically design as ordinary SP techniques (see, for example, Hensher and King, 2001). However, the design enable the researcher to precisely know at what level of parking charge the respondents will choose not to park in the area. This NO CHOICE option can then be introduced in the model although there are some discussions about no-choice option (Haaijer and Wedel, in Gustaffson et.al.,2000).

Table 1. Example of the questionnaire

Questions	Malioboro Mall (Parking destination)	Taman Garuda (Alternative 1)	Beringharjo (Alternative 2)	Choice
1	1,500	300	300	Stay
2	2,000	300	300	Stay
3	2,500	300	300	Stay
4	3,000	300	300	Alternative 1
5	3,000	500	300	Alternative 1
6	3,000	1,000	300	Alternative 1
7	3,000	1,500	300	Alternative 2
8	3,000	1,500	500	Alternative 2
9	3,000	1,500	1,000	Alternative 2
10	3,000	1,500	1,500	**Move**

3.2 The respondents

The research deals only with car drivers. The author is aware that motor cycles are dominating the road. However, they can easily find parking places since they do not take much space as cars do. The respondents are selected randomly from those who park their cars in the study area for shopping purposes and from those who would do shopping in zone 1. The total sample is 92 where 73% of the respondents visit the study area 2-3 times every month. They mostly visit the study area due to the attractiveness of the study area with respect to: the availability and variety of goods, the attractiveness for recreation, the competitiveness of the price of goods. This group accounts for approximately 70%, while the rest of the sample chooses the area due to the closeness from their origin and attractiveness of the parking facilities. The shop owners and those who are categorized as regular users were excluded.

4. MODEL ESTIMATION AND ASSESSMENT

4.1 The model

The model is a very simple model where the choice decision will only be made on the parking charge basis. This was supported by Hensher and King (2001) who stated that parking pricing is by far the superior instrument to achieve reductions in casual parking in the CBD in Sydney. The model however implicitly takes into account the walking distance since the alternative locations represent how far the walking distance would be. The utility functions for each alternative are presented as the following:

$$U(\text{zone } 1) = \underset{[2.18]}{2.257} - \underset{[-2.08]}{0.002} * CHARGE$$

$$U(\text{zone } 2) = -\underset{[-2.08]}{0.002} * CHARGE$$

$$U(\text{zone } 3) = \underset{[-9.05]}{-2.454} - \underset{[-2.08]}{0.002} * CHARGE$$

The scale parameters:

λ (zone 1) = 0.484 [1.91]

λ (zone 2) = 3.804 [1.94]

λ (zone 3) = 1.000 [fixed]

Log–L(β) = –367.007

Log–L(0) = –556.996

ρ^2 = 0.337

CHARGE is a generic variable. Alternative specific constant are applied in the utility functions for zone 1 and 3. The values between bracket below the coefficient estimates in the utility functions and after the scale parameter estimates are the t-values.

4.2 Model assessment

The evaluation of the model will consider the following criteria: a) theoretically sound (expected sign of the estimates), b) statistical fit (Rho-squared), c) significance of the variables (t-values), d) predictability, and e) flexibility of the model.

The sign of the coefficient estimates indicates the underlying theory behind the decision making process. Theoretically, CHARGE should have the negative signs, indicating that increasing CHARGE will reduce the probability of the alternative being chosen. In this respect the model produces the expected sign of estimates meaning that, theoretically, they can well explain the choice behaviour. Moreover, the significance level of variables is represented by the t-values of the associated variables. In general, the model indicated that CHARGE is highly significance.

Pseudeo R or rho-squared gives an indication of how fit the model would be. This measure is calculated as:

$$\rho^2 = 1 - [L(\beta)/L(0)] \quad \text{.......} (6)$$

where L(0) is unconstrained log-likelihood, and L(β) is the constrained log-likelihood value. Theoretically ρ^2 varies between 0 and 1. Hensher and Johnson (1981) considered that the rho-squared values between 0.2 – 0.4 is suitable for discrete choice cases based on disaggregate studies.

The model is considered to be a good model if it can predict the behaviour of population. The procedure is to compare the stated choice from the experiment and the predicted choice derived from the model. The normalized overall success index lies between 0 and 1 and represents the marginal success of the model over the straight market shares hypothesis. A value of the normalized success index between 0.2 and 0,4 indicates a good model (Young, et.al., 1983). The prediction success table is presented in the Table 2. Although the naïve success index is quite similar between the HEV and MNL (respectively 0.56 and 0.55), it does improve the normalized success index from 0.1 to 0.2 (see Nurtopo and Norojono, 2000).

Table 2. Prediction success table

	Zone 1**)	Zone 2**)	Zone 3**)	Sum
Zone 1 *)	213	98	12	320
Zone 2 *)	76	72	12	160
Zone 3 *)	21	4	2	27
Sum	310	174	26	507

*) Predicted choice
**) Actual choice

The scale parameters of the HEV model show large differences across alternatives, indicating that they have the difference variances. It supports the theory that the HEV model is a flexible model by allowing difference variances across alternatives. The scale parameter for parking in the zone 1 (0.484) implies less random component variance than parking in the zone 2 and zone 3 (respectively 3.8 and 1.0).

4.3 Parking charge elasticity estimates

Given that β_k is the estimated utility parameter on the *k*th variable (assumed to be generic), the corresponding direct-elasticity for alternative *i* with respect to a change in x_{ki} is given as the following:

$$\eta_{x_{ki}}^{P_i} = \left[\frac{\partial P_i}{\partial V_i} / P_i\right] * \beta_k * x_{ki} \qquad (7)$$

The diagonal values in the Table 3 are the direct elacticities while the others are cross elasticity estimates. The increasing parking charge in zone 1 of 1% will decrease the probability of zone 1 being chosen by 0.846%. On the other hand, it increases the probability of zones 2 and 3 will be chosen by 1.238% and 0.853% respectively (see Table 3). In the case of mutinomial logit model, the direct elasticity of zone 1 would have been –0.72%; it would then be identically distributed across the rest of alternatives. It leads to the increases of the probability for zones 2 and 3 being chosen by both 0.871% (see Nurtopo and Norojono, 2000). From theoretical point of view, the HEV provides a more realistic behaviour where the probability for choosing zone 2 is greater than for choosing zone 3 since zone 2 is closer to the shopping destination. In this case, the MNL model may lead to underestimate of people choosing zone 2, on the other hand, come up with overestimates of people choosing zone 3. Using nested logit model, Hensher and King (2001) found the direct parking charge elasticity estimates in Sydney between –0.476 and –1.015.

Table 3. Elasticity estimates for CHARGE

	Zone 1	Zone 2	Zone 3
Zone 1	-0.846	1.238	0.853
Zone 2	0.166	-0.512	0.252
Zone 3	0.014	0.057	-0.358

5. THE EFFECT OF PARKING CHARGE DIFFERENTIATION

The model can be used to predict the car driver's behaviour with respect to different parking charge policies. It is a common policy that a higher parking charge is applied to the closest place to the shopping destination (see, for example, Verhoef et.al., 1995). This is to reduce a number of cars entering the city centre.

Figure 2 demonstrates the effect of different parking charge in zone 1 by keeping parking charge at other zones remain the same as the existing condition. It is clear that, most of the car drivers will move to zone 2. Only small part of the car drivers is willing to park in zone 3. Setting parking charge in Zone 1 to be approximately Rp. 1500 will make car drivers are equally distributed among Zone 1 and Zone 2. Approximately 45% of the car drivers are willing to walk for the distance of 100-300 m if the difference in parking charge is about Rp. 1200,-

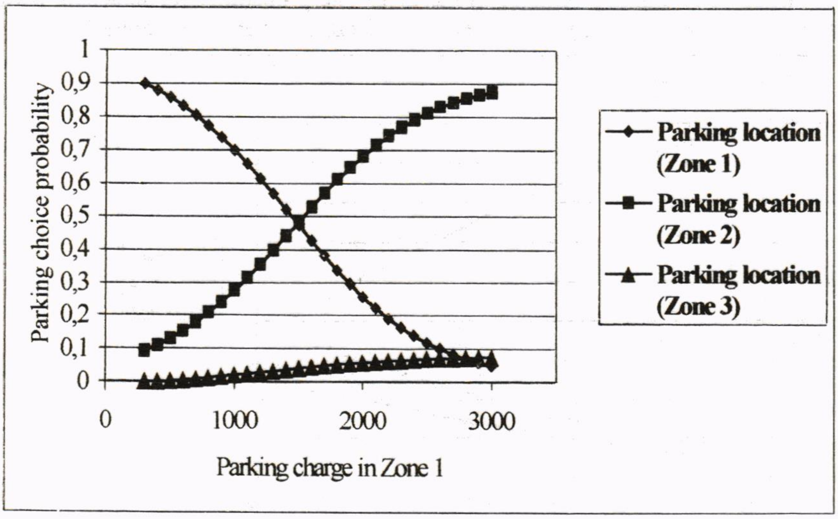

Figure 2. The effect of parking charge in zone 1 on the parking location choice

If the Municipality of Yogyakarta wants to have more cars parking in the fringe of CBD, the parking charges in zone 1 and zone 2 must be increased simultaneously. Figure 3 simulates the choice behaviour if the parking charges in zone 1 and 2 are increased. The three lines indicates how the car drivers respond to different parking charges in zone 2, given that parking charge at zone 1 is set Rp. 3000,-. Simulation takes the values that the drivers or shoppers will remain do shopping in the area. Setting parking charge at zone 2 more than Rp. 1500, for example, will make most of the shoppers leaves the shopping area to other destinations.

Table 4. Parking location choice probability

Charge at zone 2 (Rp)	Zone 1*)	Zone 1**)	Zone 2*)	Zone 2**)	Zone 3*)	Zone 3**)
300	0.258	0.049	0.683	0.875	0.059	0.075
500	0.329	0.068	0.596	0.828	0.075	0.104
700	0.406	0.093	0.502	0.767	0.092	0.141
900	0.482	0.122	0.408	0.692	0.110	0.186
1,100	0.554	0.157	0.320	0.606	0.126	0.238
1,300	0.616	0.194	0.244	0.512	0.140	0.294
1,500	0.668	0.231	0.181	0.418	0.152	0.351

Remarks:
*) Parking charge at zone 1 is held Rp. 2000,-
**) Parking charge at zone 1 is kept Rp. 3000,-
Parking charge at zone 3 is Rp. 300,- for all cases

Table 4 shows the effect of parking charge in Zone 2 on the choice probability given two parking charge levels in Zone 1. Increasing parking charge in Zone 1 from Rp. 2000 to Rp. 3000, given that parking charge in Zone 2 to be Rp. 1100, would cause a reduction of choice probability for Zone 1 from 55% to 15%. This will increase the probability for Zone 2 being chosen from 32% to 60% and also increase the attractiveness of Zone 3 from 12% to 24%.

The ultimate strategy to reduce traffic entering the city centre and making a better utilization of parking spaces while keeping shoppers remain in the Malioboro area is to increase parking charges to Rp. 3000 and Rp. 1500 in zone 1 and 2 respectively. This strategy would result in almost equal distribution of parking vehicles in the area. The probability for choosing parking locations in each zones is (see Table 2): 0.23 (zone 1), 0.42 (zone 2), and 0.35 (zone 3).

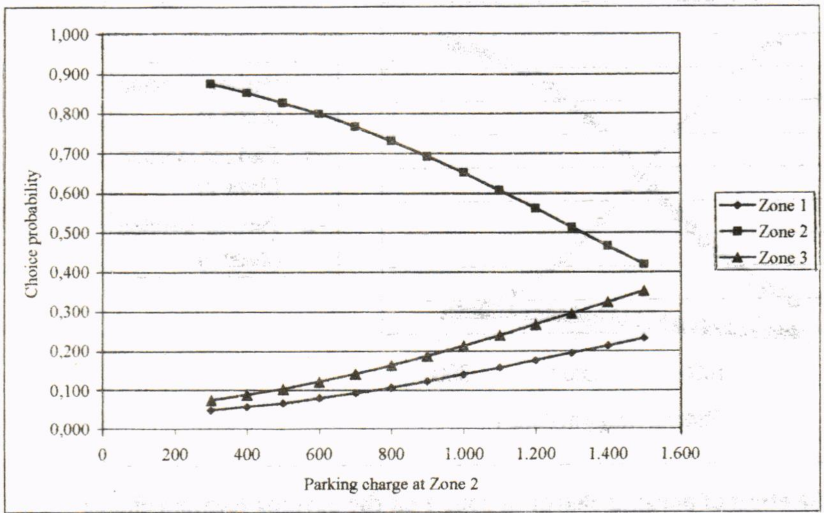

Figure 3. The effect of parking charges in Zone 2 on the parking choice (setting parking charges at Zone 1 Rp. 3000 and at Zone 3 Rp. 300)

The model can be used to establish appropriate policy measures given as a set of objectives and constraints. However, careful considerations should be taken with regards to the type of model since it can be critical. Figure 4 shows the difference of probability estimates on choosing zone 3 between HEV and multinominal logit (MNL). It has been discussed earlier that the MNL may lead to the either underestimate or overestimates the people's choice. This clearly demonstrates that if the parking charge at zone 1 is increased up to Rp 2000, there will be an increase of probability for zone 2 being chosen from approximately 10 % to 40% if MNL is employed. However, the use of HEV will result in the probability of about 70%. This would the other way around for zone 3 (not shown in the paper). From theoretical of view, if the parking charge in zone 1 increase, some people will change their parking place either in zone 2 or zone 3. Theoretically, more people will choose zone 2 rather than zone 3 since it is closer to the shopping destination. In this case HEV model replicates better than MNL model. This proofs that, in this case, the use of the model type is critical because it may result to the large differences.

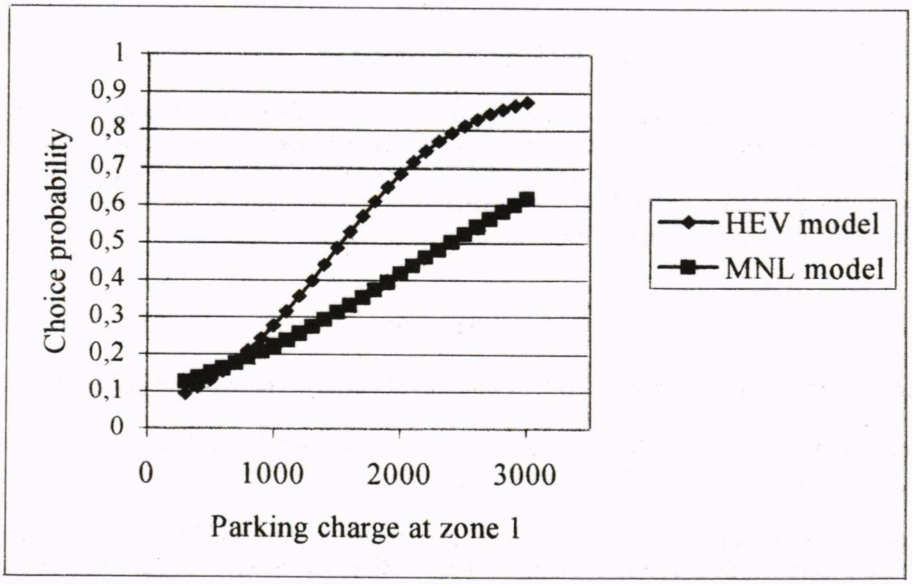

Figure 4. The effect of different models in the choice probability of zone 2

6. CONCLUSIONS AND RECOMMENDATIONS FOR FURTHER RESEARCH

Parking location problem can well be formulated as a choice problem. HEV model utilized in this research demonstrates that parking charge is an important factor in the decision making on parking choice location in the city centre of Yogyakarta. The model predicts that 1% increase of parking charge at the core would result in the reduction of choice probability at the core area by 0.846 %, and increasing the choice probability of the medium distance locations and the fringe locations by 1.238 % and 0.853 % respectively.

Charging car drivers with the same rate (for example Rp 500) in the study area would of course create traffic congestion problems since every one wants to park their cars in the core area. Differentiating parking charge spatially may result in the more balance distribution of parking demand. Increasing parking charge in the core area (zone1) up to Rp 3000, and in zone 2 of Rp. 1500, while keeping parking charge at the fringe (zone3) Rp 300 will result in the probability of zone 1, 2 and 3 being chosen of 25%, 40% and 35% respectively. Introducing parking charges beyond these values will change the result since many shoppers decide not to go to the area of study.

The paper shows the effect of model types on the result. This issue could be critical in this case and therefore should then be more elaborated. Expanding the number of data set could enrich the model specification. This could include, for example, context variables of the trips such and socio-economic variables of the respondents. Further analysis can also be done for including no-choice option in the choice set. Taking public transport as an alternative would probably not be appropriate for the area under study since public transport, hypothetically, is not an alternative for car drivers. Further investigation could also be done with regard to the peaking characteristics. People may behave differently when they are confronted with different peaking characteristics. Parking capacity restraint could also be another research interest.

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