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ROUTE DIVERT BEHAVIOR IN JAKARTA ELECTRONIC ROAD PRICING POLICY IMPLEMENTATION

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ABSTRACT

The effectiveness of transportation demand management policy depends on how commuters respond to it. This study attempts to comprehend commuter behavior in choosing routes based on electronic road pricing (ERP) policy implementation on the Sudirman and Kuningan corridors. The experiments were conducted using the data collections from a stated preference experiment in which each commuter makes a route choice with an alternative representing a hypothetical situation with a combination of tariffs and travel time in ERP policy implementation. Logit models found that the individual and household variables influence route divert behavior. A commuter with a higher income or more family members living together is more likely to have less flexibility in diverting route. In addition, the distance of the trips affected their route divert behavior and influenced an individual trip chain constrained in time-space prism.

Keywords: Electronic road pricing; Route choice; Stated preference; Transport demand management; Travel behavior

1. INTRODUCTION

The supply-side approach, which includes approaches such as expanding transportation infrastructure, had been considered the principal solution for the congestion problem in earlier days, but nowadays is no longer feasible because of limitations in funds, available land, or political support, especially in urban areas (Yamamoto et al., 2000). With all its limitations, it is already well understood that the demand-side approach i.e., Transport Demand Management (TDM) is more preferable (Kitamura, 1988). Congestion pricing is considered one of the most promising TDM schemes that may cause travelers to modify their routes, means of travel, departure times, or even activity engagement (Yamamoto et al., 2000).

The effective implementation of congestion pricing is strongly supported by planning, systems, and operations and is very connected with the relationship between the user and the operator (Mahendra, 2008). The basic concept implementation of congestion pricing is that it is subject to tariffs for commuters that are contributing to congestion in specific segments or areas. It is argued that tariff is a factor that influences commuters' decisions in arranging their trip and their travel behavior pattern (Jaensirisak et al., 2005). It is well known that one of the important aspects that influence the effectiveness of road pricing policies is if commuters accept them. The potential effectiveness of TDM schemes i.e., electronic road pricing (ERP) depends on how users respond to them (Gärling, 2005). An understanding of the decision of each

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individual is essential in the implementation of TDM policies (Kitamura, 1988; Gärling, 2005). People make their travel decision based on existing transport policy. Their decision will influence their daily travel behavior (Susilo, 2005).

Studies on road pricing have been completed in developed countries: Washbrook et al. (2006) analyzed the effect of road pricing implementation on modal choice in Vancouver; Seik (2000) evaluated the implementation of ERP on demand management in Singapore; Small and Gomez-Ibañez (1998) studied the implementation of congestion pricing in Singapore, Hong Kong, and Stockholm; and Yamamoto et al. (2000) examined patterns of allocation of time traveling performers on the application of congestion pricing in Osaka and Kobe. However, a study of commuter perception and commuter regard of road pricing policy based on willingness to pay, departure time, route selection, and mode choice has not been completed in developing countries. This study attempts to comprehend the behavior of the commuters in choosing routes on ERP policy implementation. The perception and decision of individual travel behavior needs to be explored by studying the components that affect it. Furthermore, understanding of perception and the decision of the individual regarding travel decisions is expected to become the basis for better ERP policy implementation in the future.

2. METHODOLOGY

2.1. Individual Decision Approach

Modeling travel behavior is a key aspect of demand analysis, where aggregate demand is the accumulation of individuals' decisions (Ben-Akiva & Lerman, 1985). Individuals make choices in a wide variety of decision contexts and their choices are influenced by habit, inertia, experience, advertising, peer pressures, environmental constraints, accumulated opinion, household, and family constraints (Louviere et al., 2000). Choice behavior also can be characterized by a decision process, which is informed by an interaction between perceptions and beliefs based on available information, and influenced by affect, attitudes, motives, and preferences that produce a choice (Ben-Akiva et al., 1999). A proposed framework for the choice process is that an individual first determines the available alternatives and then evaluates the attributes of each alternative relevant to the choice under consideration. Finally, the individual then uses a decision rule to select an alternative from among the available alternatives (Ben-Akiva & Lerman, 1985). Under certain technical conditions, including completeness and transitivity, preferences can be represented by a numerical indicator of scale, or utility.

A number of possible rules fall under the purview of rational decision processes (Ben-Akiva & Lerman, 1985). One of the decision rules is utility maximization (Louviere et al., 2000; Hensher et al., 2005; Koppelman & Bhat, 2006). The utility maximization concept consists of two fundamentals rule of human decision process. First, individuals' utility in each alternative(s) is characterized by scalar utility vector. Second, the individual choosing the alternative based on maximum utility value (Koppelman & Bhat, 2006).

2.2. Model Concept

The route divert model is associated with the characteristics of the individuals and the characteristics of the ERP scheme. Therefore, an individual chooses the route to maximize the utility associated with the alternatives and their characteristics. The characteristics of utility functions are: (a) related to individuals' characteristics e.g., gender, income, age; (b) related to the alternative(s); and (c) interaction between attribute of alternatives and individuals characteristics (Koppelman & Bhat, 2006). Let the total utility be the sum of the utility components.

$$U_{ti} = U_{St} + U_{Xi} + U_{St,Xi} \quad (1)$$

where;
U_{ti} : the systematic portion of utility of alternative *i* for individual *t*,
U_{St} : the portion of utility associated with characteristics of individual *t*,
U_{Xi} : the portion of utility of alternative *i* associated with the attributes of alternative *i*,
$U_{St,Xi}$: the portion of the utility that results from interactions between the attributes of alternative *i* and the characteristics of individual *t*.

Adding an error term, ε represents those components of the utility function that are not included in the model and U_{Ti} is the total utility of alternative *i*:

$$U_{Ti} = U_{ti} + \varepsilon_i \quad (2)$$

The error term is included in the utility function to account for the fact that the analysis is not able to completely and correctly measure or specify all attributes that determine travelers' mode utility assessment. By definition, error terms are unobserved and unmeasured (Hensher et al., 2005; Koppelman & Bhat, 2006). With the assumption of error that distribution components are distributed Gumbel extreme value type I, (see McFadden, 1973; Louviere et al., 2000) the basic logit equation is as follows:

$$P_{r(i)} = \frac{expU_{Ti}}{\sum_j^i U_{Tj}} \quad (3)$$

where;
P_{ri} : the probability of the individual choosing alternative *i*,
U_{Tj} : the systematic component of the utility of alternative *j*.

There are limitations in measuring every coefficient of alternative utility functions. However, to establish utility functions measurement easier, according to Koppelman and Bhat (2006) it could be done by using a reference alternative as a single constraint on each set of parameters to zero, and re-interpret the remaining components to show the differences between reference alternative and other alternative(s). Furthermore the Maximum Likelihood Estimation (MLE) method determines all coefficients in new utility function that formulate the logit model equation (see Koppelman & Bhat, 2006; Hensher et al., 2005; Greene, 2008).

2.3. Stated Preference Approaches

Stated preference (SP) techniques are considered one of most significant methodological developments for travel behavior research (Polak & Jones, 1997). Further development and better understanding of the dynamic aspect of individuals' decisions are major challenges for behavioral research. The applications of SP are widely used in travel behavior research, especially in urban areas that include residential choice, mode choice (Koppelman & Bhat, 2006), parking choice, and route choice (Yamamoto et al., 2000). This can lead to significant changes in product or service design, pricing strategy, distribution-channel and communication-strategy selection, as well as public welfare analysis (Louviere et al., 2000).

Essentially, the SP approach is used to identify behavioral responses to choice situations that are not revealed in the market and to draw conclusions regarding individuals' preferences or behavior based on responses elicited under hypothetical situations (Polak & Jones, 1997; Rose & Bliemer, 2012). An important process in the research planning of the SP method is to design the questionnaire. The combinations of attributes in all alternatives are established based on orthogonal design method that formed to representing the hypothetical situations (see Kacker et al., 1991; Hensher et al., 2005).

2.4. Data in Route Choice Analysis

Data for this analysis was obtained from a questionnaire using an SP approach under hypothetical situations in which alternative ERP schemes are implemented on the Sudirman and Kuningan corridors. In addition, personal attributes including socio-demographic and travel characteristics are included in the questionnaire. Hypothetical ERP was presented to the respondents with a certain price and the travel time on ERP corridors reduced during the pricing hours and the anticipated travel time by surface streets increased based on Yamamoto et al.'s (2000) study. The decrease and increase of travel time are converted based on a hypothetical situation from the questionnaire and combined with existing travel time based on a study by Transport Department of DKI Jakarta for the analysis afterward. The experimental design involving two attributes with three levels each, as shown in Table 1, was used to describe the hypothetical situations.

Table 1 Attributes and level on experimental design

Attributes	Level		
ERP tariff (rupiah)	12,000	18,000	24,000
Decrease in travel time of ERP streets (minutes)	10	20	30
Increase in travel time of surface streets (minutes)	10	20	30

By using an orthogonal array of the Taguchi design, we find there are three attributes, and the level of each attribute is three, so the obtained minimum number set combination is nine. Furthermore, the specified number of sets of combinations is nine, which formed a set of orthogonal arrays that conducted with Statical Package for Social Sciences (SPSS) software (Hensher et al., 2005). The hypothetical situation in the questionnaire is divided between morning and evening ERP period, with nine scenarios of hypothetical situations. The choice of route is divided by choice to remain in the ERP corridors or to divert to route alternatives. The route alternatives for every corridor are described in Figure 1.

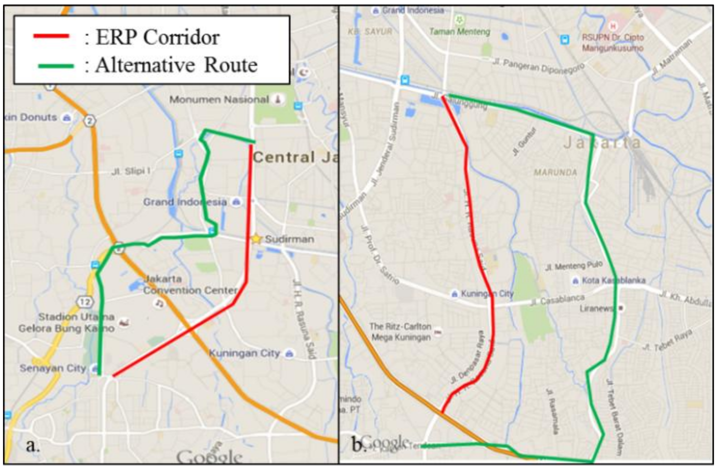

Figure 1 Description of route divert sudirman ERP (a.) Kuningan ERP (b.) Corridor

The final design of the orthogonal array combination is checked by Pearson correlation to review the collinearity between the attributes. The values of Pearson correlation are found 0.000 on each attribute, so that it can be concluded that the correlation between the independent attributes is very small. A flexible sample size method is used to determine the sample size and also to obtaining optimal data variation. Hensher et al. (2005) stated that the standard is that every option needs to be chosen by a minimum of 50 individuals. With two choices in every SP questions, the 100-questionnaire sample size is acceptable to maintain population variance. The survey was conducted from June 9 to June 12, 2015. Respondents were collected by being personally approached in the area around the Sudirman and Kuningan ERP corridors by six surveyors. After reviewing the data completeness and consistency, only 93 sets can be used for further analysis. Explanation regarding the model evaluation and interpretation of the models are refer to Hosmer and Lemeshow (2000), Koppelman and Bhat (2006), Hair et al. (2006), Greene (2008).

3. RESULTS

3.1. Data Description

Males comprised 64% of respondents, and the age distribution was dominated by (52%) moderate-age commuters (e.g., ages 24 to 35). Regarding income of commuters, 42% of the respondents have a 4–6 million rupiah income. In the terms of travel characteristics, the majority of commuters have to travel a distance less than 10 km (43%) or 10–20 km (37%) from their home to the activity location. A description of the type of trip chain showed that 43% complete simple trip chains and 57% perform complex trip chains. A comparison analysis was conducted to explore travel distance from home to activity location based on gender, type of trip chain, and ERP corridor, as shown in Table 2. The test results found there was a significant difference in the travel distance between genders, and between the ERP corridors. However, no significant differences were found when the trip distance was compared between types of trip chain.

Table 2 Distribution of travel distance from home to activity location

Travel Distance	Gender		Trip Chain		ERP Corridor	
	Male	Female	Simple	Complex	Kuningan	Sudirman
< 10 km	25%	18%	20%	23%	13%	30%
10–20 km	25%	12%	15%	22%	22%	15%
> 20 km	14%	6%	8%	12%	14%	6%
[χ^2; df; p-value]	[10,421; 2; 0,005]		[3,430; 2; 0,180]		[100,888; 2; 0,000]	

3.2. Model of Route Divert Estimation

The route selection model estimation was established to identify the characteristics of respondents and the attributes associated with route characteristics that were expected to influence the pattern of route selection in ERP policy implementation in a logistics model. Previous studies found (Yamamoto et al., 2000; Susilo, 2005; Brunow & Gründer, 2013) that the characteristics of socio-demography (e.g., household, age, income, gender) and characteristics of the corridors (e.g., length, travel time) affected route choice behavior of individuals'. Therefore these models are conducted based on hypotheses that determination of the ERP policy implementation should be considering interaction between individuals' and corridors characteristics.

Table 3 shows the route divert model estimation and the results of model quality. The significance of the Omnibus test results of the model coefficients smaller than 0.05 in both models and the Hosmer–Lemeshow test shows the p-value is much greater than 0.05. It can be concluded that the predictions of the model did not significantly differ from the observations. The value of Cox and Snell R^2 and Nagelkerke R^2 indicate that the model can account for roughly one-third of the data variation between the two groups selected mode. As a whole, for the model selection in the ERP implementation, morning and afternoon times are able to correctly predict more than 65% data variation based on a cross-tabulation test.

Table 3 Parameter Estimate of Route Divert Choice Model

Variables	Morning ERP Implementation		Evening ERP Implementation	
	β	p-value	β	p-value
Constant	-0.4111	0.5323	-0.6966	0.2923
ERP tariff	-0.0001	0.0000	-0.0001	0.0000
Difference of travel time between the route	-0.0434	0.0000	-0.0558	0.0000
Male commuters [D]	0.379	0.0283	0.2341	0.1929
Less than 25 years old commuters [D]	-0.2906	0.3335	-0.2217	0.4622
More than 35 years old commuters [D]	-0.3936	0.0478		
Commuters income < 2 million rupiah [D]	-0.4807	0.1083	-0.349	0.245
Commuters income > 6 million rupiah [D]	0.4021	0.0658	0.3019	0.1871
Number of family who lived together = 0–1 person [D]	-0.2591	0.3339		
Number of family who lived together > 3 person [D]	0.282	0.1194	0.2981	0.1006
Position in home = Children [D]	0.8354	0.0014	0.6366	0.0148
Number of route alternative = 1 [D]			-0.0358	0.8864
Number of trip frequency per day = 2 [D]	0.1253	0.4552	-0.2056	0.2326
Sudirman ERP corridor [D]	-1.0609	0.0000	-0.3235	0.0791
Commuters trip distance > 20 km [D]	0.3646	0.0629	0.3903	0.0573
Hosmer and Lemeshow test [$\chi2$; df; p-value]	[8.171; 8; 0.417]		[2.690; 8; 0.952]	
Omnibus tests of model coefficients [$\chi2$; df; p-value]	[135.476; 13; 0.000]		[168.823; 12; 0.000]	
[-2LL; Cox and Snell R^2; Nagelkerke R^2]	[1063.620; 0.142; 0.192]		[995.328; 0.174; 0.238]	
[Percent correct]	67.60%		69.50%	

*D = 1 if yes, 0 otherwise; Choice 1 = ERP Route; 0 = otherwise

The commuter's characteristics, such as income and number of household members, influenced route choice pattern. Travelers with an income of less than 2 million tend to divert, whereas commuters with income of more than 6 million were more likely to remain on the ERP route. In addition, for the household characteristics, we found that the commuters who live with more than three family members were more likely to remain on the ERP route, which is partly consistent with the findings on previous studies of family characteristics that affect travel behavior (Susilo, 2005; Brunow & Gründer, 2013). This is supposedly related to the various activity needs between each family member that affect travel patterns of other family members. Variables that are highly significant in influencing the traveling public in the ERP periods (i.e., morning and evening) are ERP tariff and travel time. These are very logically related to variable rates and travel time, which have a direct impact on the individual, as findings in previous studies found (Yamamoto et al., 2000). In addition, the route divert model discovered that several significant variables in the application of ERP morning or evening need to be divided to disaggregate models. It was found that ERP corridor location has a tendency to affect corridor route selection patterns. Different characteristics of commuters in each corridor are likely the reason the pattern of the route decision is different. This finding supports the reason that the models should be classified based on the ERP corridor. Furthermore, travel characteristics of commuters' are found to affect the patterns of route choice. Variables of commuters with travel distance of more than 20 km from their residence to the location of the activity were found to have a tendency to remain in the ERP. This finding relates to the flexibility of route choice, which is influenced by travel distance. This needs to be analyzed further by a classifying model of route selection based on travel distance.

3.3. Model of Route Divert based on Travel Distance Estimation

The route divert model based on travel distance formed by classified the model of route divert based on the commuters travel distance (e.g., < 10 km, 10–20 km, and > 20 km) in both of ERP corridors (e.g., Sudirman and Kuningan) to draw the effect of travel length and corridors characteristics to route choice behavior. The different characteristics (e.g., length, number of intersection, land use, side friction) between Sudirman and Kuningan were expected to influence the route decision, as the information regarding these choice models is useful to determine the ERP corridors more effectively in the future. The conditional logit model is established based on the characteristics of the utility that varies based on each alternative (see Koppelman & Bhat, 2006; Greene, 2008). Analysis and interpretation of the model is based on Hensher et al. (2005), Koppelman and Bhat (2006), and Greene (2008).

The quality of this model can be seen from the comparison between constant likelihood and estimate models likelihood, namely the Log-Likelihood (LL) ratio test. Results of the LL ratio test showed that the hypothesis null of a model with independent variables as good as the model without independent variables can be rejected on every model. Indicators pseudo-r^2 (ρ^2) indicate that the model can accurately predict for roughly a quarter of the data variation. In addition, cross-tabulation test results showed that more than 50% of the model could explain the data.

Table 4 shows the route divert model based on travel distance from home to activity location. It was found that every model has a negative coefficient in tariff and travel time. These findings are consistent with the early study, which found that increasing tariff or travel time will contrarily decrease the probability of individuals' choice of that route (Yamamoto et al., 2000). However, it is interesting to evaluate the coefficient of the constant in every model that indicates the different magnitude between travel distance characteristics. It is found that a commuter with a travel distance more than 20 km tends to have less flexibility to change a route than a commuter with a travel distance of less than 10 km. This shows that there is a pattern effect of travel distance to the decisions of travelers in determining route. Furthermore, comparison between the coefficients of the constant between the ERP corridors shows an interesting result. The comparison of constant coefficient magnitude between ERP corridors indicates that commuters in the Kuningan corridor are more likely to remain in the ERP corridor than commuters in the Sudirman corridor. This finding is consistent with early models' findings, as the commuters tend to choose alternative corridors in the Sudirman ERP corridor (Table 3).

Table 4 Parameter estimate of route divert choice model based on travel distance

Variables	Morning ERP Implementation		Evening ERP Implementation		Morning ERP Implementation		Evening ERP Implementation	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
	Sudirman Corridor				Kuningan Corridor			
Travel Distance < 10 km								
Constant	-2.7617	0.0006	-0.9621	0.1315	0.5313	0.6561	0.4522	0.7070
Tariff	-0.0001	0.7725	-0.0002	0.5326	-0.0002	0.0000	-0.0001	0.0024
Travel time	-0.0500	0.0000	-0.0307	0.0000	-0.0502	0.0031	-0.0403	0.0175
[L(β); ρ^2]	[-166.5928; 0.11]		[-159.5274; 0,07]		[-66.631; 0.18]		[-70.2964; 0.10]	
[-2LL;% Correct]	[37. 0028; 63%]		[21.63; 63%]		[28.72; 61%]		[15.31; 59%]	
Travel Distance 10–20 km								
Constant	-1.3730	0.2121	1.4782	0.0089	1.9171	0.0527	0.9073	0.3810
Tariff	-0.0004	0.0641	-0.0001	0.0073	-0.0003	0.0000	-0.0004	0.0000
Travel time	-0.0679	0.0002	-0.0057	0.5687	-0.0747	0.0000	-0.1306	0.0000
[L(β); ρ^2]	[-83.6982; 0.12]		[-83.6982; 0.05]		[-93.692; 0.34]		[-78.4266; 0.44]	
[-2LL;% Correct]	[19.25; 63%]		[7.93; 60%]		[96.5522; 71%]		[125.4332; 75%]	
Travel Distance > 20 km								
Constant	1.1372	0.4860	-0.4283	0.1726	1.3153	0.2816	5.2527	0.0005
Tariff	-0.0002	0.0968	-0.0002	0.4978	-0.0002	0.0000	-0.0003	0.0000
Travel time	-0.0154	0.4976	-0.0295	0.1934	-0.0419	0.0156	-0.0103	0.5800
[L(β); ρ^2]	[-37.0959; 0.10]		[-37.3929; 0.08]		[-66.864; 0,16]		[-58.0601; 0.27]	
[-2LL;% Correct]	[7.31; 52%]		[6.19; 52%]		[25.9894; 61%]		[42.977; 68%]	

* Choice 1 = ERP Route; 0 = otherwise

4. DISCUSSION

Interaction between user perception and the transport policy system is an important point to ensure ERP policy implementation is effective and efficient. This study aims to fill the gap regarding an understanding of individual route divert behavior on Jakarta ERP policy implementation. Route divert behavior is explored using a logits model, in which the explanatory variables are socio-demographic (e.g., income, age, household, etc.) and travel characteristics (e.g., travel distance, trip frequency, etc.). The early study findings were partly consistent with the findings in this study (Yamamoto et al., 2000). However, the results of analysis of this study also found an interesting result regarding the different commuter behavior between the ERP corridors.

The first route divert model found that income and household characteristics influenced route choice. Commuters who have a higher income tend to remain in the ERP route as they have high financial flexibility than commuters who have lower income. It is also found that the variable number of family members living together in a household affects the pattern of route choice. Commuters who lived with more than three family members tended to remain in the ERP route. Obviously, it can be inferred that non-single household commuters tend to travel more non-directly than those in a single number household because non-single household commuters have a certain amount of probability to travel with other related family members to various activities, which significantly affects their travel behavior. The interesting results found in the route divert models based on trip distance in both of ERP corridors. It was found that commuters who have a longer travel distance are more likely to have flexibility to change a route than commuters who have a shorter travel distance. It can be concluded that travel behavior of commuters is influenced by their travel distance, which is a fundamental theory of travel behavior as constrained in time and space. Thus, the longer an individual travel time, the more reduced their time and space flexibility. This will, therefore, eventually affect their travel behavior.

It was also found that the ERP corridors influence the route divert pattern. Commuters in the Kuningan corridor tend to remain in the ERP route, rather than commuters in the Sudirman corridor. A possible reason for this is the characteristics of ERP corridors, such as distance, number of intersections, side friction, and the structure of land use near the ERP corridors is different. The structure of the Sudirman corridor has more intersections, mixed land use, and traffic than the Kuningan corridor. The combinations between intersection and side frictions in ERP corridors leads to longer travel time where these combinations will influence individuals' attitudes in choosing routes. Thus, people tend to choose the ERP corridors that have minimum travel time and avoid adding more time or detours that reduce utility. The fundamental reason is stated by McNally and Rindt (2007) that combinations of duration, length, or stops will affect the individual activity behavior, meaning individuals tend to accomplish more activities in less time and avoid adding stops and trips. These findings reveal the effect of route characteristics information on travel behavior.

5. CONCLUSION

Various decisions of an individual affect ERP implementation scenarios and characteristics, which underline the understanding of individual behavior in making decisions, especially in the implementation of ERP policy; which should be explored in further studies. Technical planning, such as determination of ERP corridors, needs to be understood further in the context of relations with individual travel behavior. Thus, factors affecting the individual's behavior, which are dynamic and inconsistent, needs to be explored further, especially those closely related to the implementation of ERP in developing cities.

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