THE IMPACT OF PRICE CHANGE ON CONSUMER CHOICE OF AUTOMOBILES*

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Abstract

The objective of this paper is to examine whether a change in the price of a given model of national automobiles affects the choice of alternative car models by consumers. Four models of national automobiles—Saga 1.3cc, Saga 1.5cc, Wira 1.3cc, and Wira 1.5cc—are considered over the period 2000–2002. The results based on the conditional logit model indicate that all of the alternative models are substitutes to each other.

Keywords: Conditional logit, Vehicle-type choice, Saga, Wira

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1. Introduction

Malaysia is the largest passenger car market in ASEAN, with more than 500,000 cars sold annually and a car ownership ratio of 200 cars for every 1000 people.[1] As shown in Table 1,[2] the total number of new passenger cars registered in Malaysia has grown steadily from 80,420 units in 1980 to 366,738 units in 2006. This phenomenon is due in part to the rapid growth of the economy and the high purchasing power of its growing population. At the same time, the introduction and promotion of national cars by the government has increased the demand for nationally-made cars. Since their introduction in 1985, national cars have persistently dominated the domestic car market. Its dominance is clearly visible from Figure 1, where the market share of national cars grew from as low as 47 percent when they were first introduced to as high as 93 percent in 1999 and 2000. Owing to the Malaysia's participation in AFTA, however, the market share for later years has declined slightly. In the year 2006, for example, the market share of national cars has fallen to 76 percent.

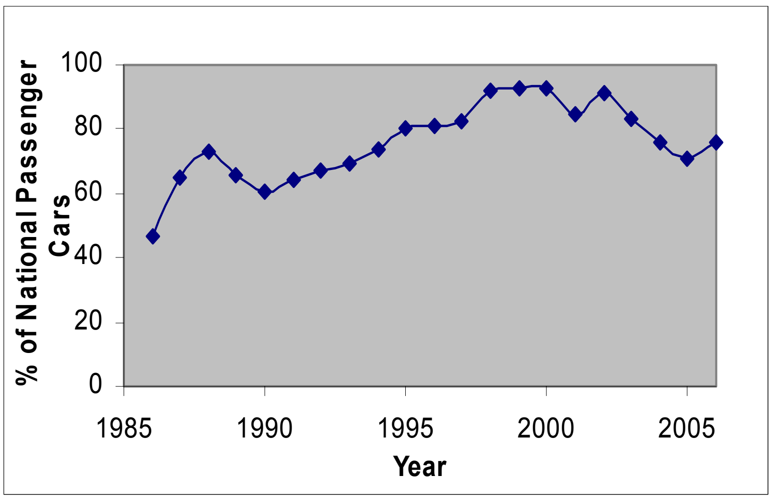

Figure 1: National Passenger Cars as a Percentage of Total Passenger Cars Registered in Malaysia, 1986–2006

Source: Malaysian Automotive Association.

Currently, there are four national car producers in Malaysia: Proton, Perodua, Naza, and Inokom. Together, these car makers have rolled out approximately 17 models of passenger cars, 8 models of commercial vehicles and 2 models of 4X4 vehicles. Proton has produced Saga (1986),[3] Wira (1993), Perdana

[1] Report on Malaysia's Automotive Industry by Malaysian Industrial Development Authority (MIDA).
[2] See Table 1 in the Appendix A.
[3] The Saga model was face-lifted in 1992 and was renamed Iswara.

(1994), Satria (1995), Putra (1995),[4] Tiara (1996),[5] Waja (2000), Gen-2 (2004), Savvy (2005), and Persona (2007). Perodua has produced Kancil (1994), Kembara (1998), Kenari (2000), Kelisa (2001), Myvi (2005) and Viva (2007). Naza has produced Sorento (2005), Citra (2005), Ria (2004), Bestari (2006), Suria (2006) and Sutera (2006). Inokom has produced Lorimas (2002), Permas (2002), Atos (2004)), Getz (2006) and Matrix (2004). All of these models differ from one another in terms of a number of features such as the size of engine (from 660cc to 2000cc), the type of design (sedan or aeroback), the type of transmission (manual or automatic) and the type of body paint (metallic or solid). Of these 27 different models, the top five best-selling cars based on the volume of production are Saga, Wira, Kancil, Waja and Kelisa. However, the top five best-selling cars based on the annual average are Wira, Myvi, Kancil, Saga and Waja.

1.1 Problem Statement

The idea behind the introduction of these alternative national car models, along with a variety of features for each model, is to cater to the needs of different segments of the car market. If this is the case, then these alternative models are said to be complementing each other. However, it could also be argued that there exists overlapping among these market segments. If this is the case, then these alternative models could be, to a certain extent, behaving like substitute goods. This paper attempts to address and answer this issue empirically by employing a vehicle-type choice model.

1.2 Scope of Research

Although there exists a relatively large menu of national automobile models in Malaysia, computational burden necessitates that we restrict the choice to a relatively few models. Accordingly, we choose the top two best-selling models based on the volume of production: Saga and Wira. Since each model comes in two engine sizes (i.e. 1.3cc and 1.5cc), the choice made by a consumer amounts to whether he or she purchases one of the following four models: Saga 1.3cc, Saga 1.5cc, Wira 1.3cc, or Wira 1.5cc.

1.3 Objective of Research

Given the range of choices available, the objective of this paper is to measure the degree in which a consumer's choice of a particular car model is affected by changes in the prices of alternative models. In other words, we seek to measure cross-price marginal effects of a price change (i.e., the marginal effect of a price change of one car model on the choice of alternative models).

[4] Putra was a failure. Its production ceased in 2000.
[5] Tiara was another failure. Its production ceased in 2001.

1.4 Significance of Research

Economists are usually concerned about consumer choices at the aggregate or market level. However, studies on consumer choices at the individual or household levels in Malaysia are lacking. This paper hopes to highlight the robust use of conditional logit models in understanding the choices made by individuals in order to maximize their utilities. The automobile market was chosen due to the availability of data provided by MAA. At the same time, with the difficult challenges currently faced by local car producers due to globalization, we hope that this paper is the beginning of a series of papers that would focus on determining the factors that affect consumer choices. Thus, we hope to contribute ideas to local car producers in becoming more competitive not only in the domestic market but also internationally. Understanding consumer needs is the only way for our local producers to survive in the globalize world.

2 Literature Review

Previously, economists and market researchers usually use aggregate data when doing market research due to the lack of analytical techniques to handle disaggregate data. Studies concerning individuals or consumers' choice patterns usually take disaggregate or individual data. At the same time, consumers tend to face a discrete rather than a continuous set of choices. Hence, many times the dependent variable is discrete, and thus not suitable to be used in a standard linear regression model. However, the development of multinomial/conditional logit model by McFadden (1973) has helped to spur research in choice models.[6] Instead of considering continuous variable as the dependent variable, a multinomial logit model only merely considers the probability that this variable takes one of the few possible choices. Since this probability is not observed but in fact only the actual outcome is observed, the logit model is more complicated than the standard linear regression model. Currently, both academics and market researchers frequently use multinomial, conditional and nested logit models to explain consumers' choice decisions.

The multinomial, conditional and nested logit models have been widely used in vehicle type choice research. It is appealing because it is based on a behavioral theory of utility. Vehicle type choice models can be grouped into two categories, vehicle ownership models and vehicle purchase models, depending on whether the chosen vehicle type is considered as already owned

[6] At this point, it is necessary to distinguish between two terms—conditional logit and multinomial logit—because it is typical to find that both terms are used interchangeably in the literature. In a conditional logit model, the explanatory variables are both individual and alternative-specific, and the coefficients are constant. However, in a multinomial logit model, the explanatory variables are individual-specific only, and the coefficients vary with alternatives. Apparently, the choice between applying a conditional logit model or a multinomial logit model in any analysis hinges upon whether one has access to individual and alternative-specific explanatory variables or just alternative-specific explanatory variables. See Long (1997), Franses and Paap (2002), or Greene (2008).

or newly bought. Many of these models differ from one another due to the different dependent and explanatory variables employed in these models. For example, Lave and Train (1979) uses ten vehicle classes (such as compact, sports, standard, luxury, etc) as the dependent variable, while the explanatory variables consist of purchase price, vehicle weight and age, number of household members and number of vehicles. Choo and Mokhtarian (2004), on the other hand, uses nine vehicle categories (such as small, compact, mid-sized, large, luxury, sports, SUV, etc) as the dependent variable, while the explanatory variables are grouped into mobility, travel liking, attitudes, personality, lifestyle and demographics. Thus, comparison of the variables involved is difficult.

However, in many models, the most common explanatory variable is the vehicle price, which tends to be negatively correlated with the dependent variable and highly significant. This means that, all else equal, the higher the price of a vehicle, the lower is the probability that the vehicle will be chosen for purchase. The evidence of this negative correlation between choice of a vehicle type/model and its own price are abundant in the literature as can be seen in Lave and Train (1979), Manski and Sherman (1980), Mannering and Winston (1985), Berkovec (1985) and Mannering et al. (2002), to mention a few.

3 Methodology and Data

Our empirical analysis is based on the conditional logit model, where the dependent variable is the choice of car models made by a consumer *i*. Let this automobile choice be represented by y_i, where

$$(1) \quad y_i = \begin{cases} 1 \text{ if } i \text{ buys Saga } 1.3cc \text{ (or } S13) \\ 2 \text{ if } i \text{ buys Saga } 1.5cc \text{ (or } S15) \\ 3 \text{ if } i \text{ buys Wira } 1.3cc \text{ (or } W13) \\ 4 \text{ if } i \text{ buys Wira } 1.5cc \text{ (or } W15) \end{cases}$$

Given the available choices, the probability of buying any particular car model *j* (j = 1, 2, 3, 4) by consumer *i* (*i* = 1, 2, …, N) is expressed by

$$(2) \quad \text{Prob}(y_i = j \mid \mathbf{x}'_{\mathbf{ij}}\boldsymbol{\beta}) = \mathbf{F}(\mathbf{x}'_{\mathbf{ij}}\boldsymbol{\beta}),$$

where F (.) is a cumulative distribution function which assumes the logistic form,

$$(3) \quad \mathbf{F}(\mathbf{x}'_{\mathbf{ij}}\boldsymbol{\beta}) = \frac{\mathbf{exp}(\mathbf{x}'_{\mathbf{ij}}\boldsymbol{\beta})}{\sum_{\mathbf{j=1}}^{\mathbf{4}} \mathbf{exp}(\mathbf{x}'_{\mathbf{ij}}\boldsymbol{\beta})},$$

and $\mathbf{x}_{\mathbf{ij}}$ is a vector of prices of various models,

(4) $\mathbf{x}_{\mathbf{ij}}^{'} = \left(x_{i1}, x_{i2}, x_{i3}, x_{i4}\right),$

where x_{i1} is the price of S13 faced by consumer i, x_{i2} is the price of S15 faced by consumer i, and so on.[7,8]

Substituting Eq.(3) into Eq.(2), we obtain the complete specification for the conditional logit model:

$$\text{(5)} \quad \text{Prob}(y_i = j \mid \mathbf{x}_{\mathbf{ij}}^{'}\boldsymbol{\beta}) = \frac{\mathbf{exp(x_{ij}^{'}\boldsymbol{\beta})}}{\sum_{\mathbf{j=1}}^{\mathbf{4}} \mathbf{exp(x_{ij}^{'}\boldsymbol{\beta})}}.$$

The cross-price marginal effects can be obtained by differentiating Eq.(2) with respect to the price variable of interest. In practice, the cross-price marginal effects are approximated by the cross-price discrete change, which can be expressed as follows:

$$\text{(6)} \quad \frac{\Delta\text{Prob}(y_i = j \mid \mathbf{x}_{\mathbf{ij}}^{'}\boldsymbol{\beta})}{\Delta x_{ik}} = \text{Prob}(y_i = j \mid \bar{\mathbf{x}}_{\mathbf{ij}}^{'}\boldsymbol{\beta}, \bar{x}_{ik} + \Delta x_{ik}) - \text{Prob}(y_i = j \mid \bar{\mathbf{x}}_{\mathbf{ij}}^{'}\boldsymbol{\beta}),$$

where the bar over the price variables indicates that the prices are evaluated at specific values (usually their mean values). The cross-price discrete-change can help us answer the following questions:

- What is the impact on the probability of buying S13 by consumer *i* of a 10% increase in the price of a) S15, b) W13, or c) W15?

- What is the impact on the probability of buying S15 by consumer *i* of a 10% increase in the price of a) S13, b) W13, or c) W15?

- What is the impact on the probability of buying W13 by consumer *i* of a 10% increase in the price of a) S13, b) S15, or c) W15?

The cross-price discrete change can be positive or negative, depending on whether the models under consideration (say, S13 and W13) are substitutes or complements. If they are substitutes (complements), then an increase in the price of W13 is expected to have a positive (negative) impact on the choice of S13, and vice versa. Accordingly, the sign of the cross-price discrete change (there are 9 of them) conveys information on whether two models are substitutes or complements.

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[7] Note that each x_j is indexed by i to account for the possibility that the price of a given model faced by a consumer may differ from that faced by another consumer.

[8] An implicit assumption embodied in Eq.(3) is that all price variables share a common slope parameter but different intercept terms. For identification, the intercept term for x_{i4} is assigned the value of zero.

Furthermore, the magnitude of the cross-price discrete change sheds light on the degree of substitutability or complementarity of any two models. For example, if a 10 percent increase in the price of S15 raises the probability of buying S13 by 5 percent and a 10 percent increase in the price of W13 raises the probability of buying S13 by 15 percent, then W13 is a closer substitute to S13 than S15 is.

The data required for this analysis were obtained from the office of the Malaysian Automotive Association (MAA) in Petaling Jaya. Although the quantity data for automobiles are generally available for the period 1986–2006, the car price data are missing for some models during certain years. In our case, the paucity of price data for both Saga and Wira models has forced us to restrict the period of analysis to 2000–2002. During this period, the total quantity sold of all four models was 92,138 units. Of this figure, the most popular model was W15 (57.4 percent), followed by S13 (22.1 percent), S15 (10.9 percent), and finally W13 (9.6 percent). The breakdown of the quantity sold of these models by years is given in Table 2.

Table 2: Quantity of Saga and Wira Models Sold, 2000–2002

	Saga		**Wira**	
Year	**1.3cc**	**1.5cc**	**1.3cc**	**1.5cc**
2000	8,126	4,558	2,211	17,260
2001	8,596	3,110	3,333	16,915
2002	3,643	2,363	3,295	18,728
Total	20,365	10,031	8,839	52,903

Source: Malaysian Automotive Association

In a conditional logit model with J choices, every purchase made by a consumer is recorded as 1×J observations (since a consumer observes the prices of all four models before he or she chooses one particular model). Hence, if there are N purchases made, then the total number of observations is equal to N×J. In our case, N = 92,318 and J = 4;[9] hence, the total number of observations is equal to 368,552! In view of the fact that the storage capacity for Microsoft Excel is about 65,000 observations, we scaled down the number of purchases to 1 percent (i.e., N = 921 units). In doing so, we ensure that the number of purchases for each model is reduced by 1 percent, too.

4 Empirical Results

Given the data, we conduct a conditional logit analysis of S13, S15, W13, and W15 during the period 2000–2002 based on the maximum likelihood method. As reported in Table 3, the results show that a) the intercept coefficients (i.e.,

[9] Note that we assume one consumer buys one unit of cars only; there is no repeat purchase. In view of the car price and the short time period, this is a plausible assumption to make.

the estimated coefficients on the first three car models)[10] enter with the negative signs and significant at the 1% level, and b) the (common) slope coefficient (i.e., the estimated coefficient on the price variable) enters with the negative sign and significant at the 1% level. The significance of the intercept terms suggests that all of those models are distinct from each other, whereas the significance of the slope term implies that price changes are expected to have a significant effect on the choice of any one model. In addition, the negative sign of the intercept terms suggests that W15 is the most popular model on the road, and the negative sign of the slope coefficient indicates that the own-price marginal effects are negative.

Once we have confirmed the sign and significance of the estimated parameters, we proceed with the cross-price discrete change analysis. As documented in Table 4, the general result is that an increase in the price of any one model has a positive effect on the probability of buying any other alternative models. This result suggests that all of those models are substitutes to each other.

Table 3: Estimates of Intercept and Slope Coefficients

Variables	Coefficient	Std Error	z
S13	–13.0436*	3.6021	–3.62
S15	–8.7237*	2.1116	–4.13
W13	–10.5320*	2.6181	–4.02
Price	–1.0878*	0.3241	–3.36

Note: The asterisk * indicates that the coefficient is significant at the 1% level.

Once we have confirmed the sign and significance of the estimated parameters, we proceed with the cross-price discrete change analysis. As documented in Table 4, the general result is that an increase in the price of any one model has a positive effect on the probability of buying any other alternative models. This result suggests that all of those models are substitutes to each other.

The specific results can be decomposed into the cross-price discrete change on S13, S15, and W13. For S13, we find that a) a rise in the price of S15 by RM1000 raises the probability of buying S13 by 2%, b) a rise in the price of W13 by RM1000 raises the probability of buying S13 by 0.85%, and c) a rise in the price of WS15 by RM1000 raises the probability of buying S13 by 13.7%.

[10] Recall that the intercept term for the reference category, W15, is set to zero.

Table 4: Cross-Price Discrete Change

Independent Variable	Dependent Variable		
	S13	S15	W13
S13	–0.1260* (–5.54)	0.0210* (4.15)	0.0095* (8.06)
S15	0.0200* (4.17)	–0.0836* (–4.09)	0.0058* (6.19)
W13	0.0085* (8.14)	0.0055* (6.67)	–0.0388* (–9.47)
W15	0.1369* (3.63)	0.0878* (2.83)	0.0396* (5.76)

Note: The z-values are in parentheses. The asterisk * indicates that the coefficient
is significant at the 1% level.

For S15, we find that a) a rise in the price of S13 by RM1000 raises the probability of buying S15 by 2.1%, b) a rise in the price of W13 by RM1000 raises the probability of buying S15 by 0.55%, and c) a rise in the price of WS15 by RM1000 raises the probability of buying S15 by 8.78%.

For W13, we find that a) a rise in the price of S13 by RM1000 raises the probability of buying W13 by 0.95%, b) a rise in the price of S15 by RM1000 raises the probability of buying W13 by 0.58%, and c) a rise in the price of WS15 by RM1000 raises the probability of buying W13 by 3.96%.

Finally, we may also conduct the own-price discrete change analysis. We find that a) a rise in the price of S13 by RM1000 reduces the probability of buying it by 12.6%, b) a rise in the price of S15 by RM1000 reduces the probability of buying it by 8.36%, and c) a rise in the price of W13 by RM1000 reduces the probability of buying it by 3.88%. All of these results are consistent with the predictions of demand theory.

5 Conclusions

Our empirical results lead us to the following conclusions. First, at the broad level, we find that all of the car models that we analyzed are substitutes to each other. Second, at a somewhat narrower level, we find that the closest substitute to S13, S15, and W13 is W15; of the three, S13 is the closest substitute to S13.

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Appendix A: Table 1

Table 1: Quantity of Cars Registered in Malaysia, 1980–2006

Year	Passenger Cars	Commercial Vehicles	4x4 Vehicles	Total Vehicles
1980	80,420	16,842	-	97,262
1981	86,444	14,491	-	100,935
1982	86,245	15,588	614	102,447
1983	90,251	15,691	2,372	108,314
1984	86,810	19,856	3,249	109,915
1985	63,857	26,742	4,400	94,999
1986	47,028	18,294	2,525	67,847
1987	35,265	12,269	1,462	48,996
1988	53,532	15,638	2,422	71,592
1989	73,793	31,124	4,440	109,357
1990	106,454	51,420	7,987	165,861
1991	121,660	49,683	10,534	181,877
1992	109,432	29,399	6,253	145,084
1993	128,600	31,283	8,045	167,928
1994	155,765	33,974	10,696	200,435
1995	224,991	47,235	13,566	285,792
1996	275,615	69,444	19,729	364,788
1997	307,907	70,334	26,596	404,837
1998	137,691	17,641	8,519	163,851
1999	239,647	26,171	22,729	288,547
2000	282,103	33,732	27,338	343,173
2001	327,447	37,623	31,311	396,381
2002	359,934	42,727	32,293	434,954
2003	320,524	50,882	34,339	405,745
2004	380,568	70,948	36,089	487,605
2005	416,692	97,820	37,804	552,316
2006	366,738	90,471	33,559	490,768

Source: Malaysian Automotive Association (MAA) website.

Appendix B: Calculation of Cross-Price Discrete Change

To calculate the cross-price discrete change, let us expand Eq.(5) as follows:

$$\text{(A)}\quad \text{Prob}(y_i = j \mid \mathbf{x}'_{\mathbf{ij}}\boldsymbol{\beta}) = \frac{\exp(\beta_{0j} + \beta_1 x_{ij})}{\exp(\beta_{01} + \beta_1 x_{i1}) + \exp(\beta_{02} + \beta_1 x_{i2}) + \exp(\beta_{03} + \beta_1 x_{i3}) + \exp(\beta_{04} + \beta_1 x_{i4})},$$

where the denominator consists of the sum of the exponential function of all four car models and the numerator contains the exponential function of car model j. Note that the intercept terms vary across car models but the slope parameters are constant. For identification, the intercept term for W15 (i.e., j = 4) is set equal to zero, $\beta_{04} = 0$.

Setting $\beta_{04} = 0$, then the probability of buying S13 (i.e., $j = 1$) by consumer i is given by

$$\text{(B)}\quad \text{Prob}(y_i = 1 \mid \mathbf{x}'_{\mathbf{ij}}\boldsymbol{\beta}) = \frac{\exp(\beta_{01} + \beta_1 x_{i1})}{\exp(\beta_{01} + \beta_1 x_{i1}) + \exp(\beta_{02} + \beta_1 x_{i2}) + \exp(\beta_{03} + \beta_1 x_{i3}) + \exp(\beta_1 x_{i4})}.$$

Suppose we want to measure the impact of a change in the price of S15 (j = 2) on the probability of buying S13. The cross-price discrete change is given by

$$\text{(C)}\quad \frac{\Delta\text{Prob}(y_i = 1 \mid \mathbf{x}'_{\mathbf{ij}}\boldsymbol{\beta})}{\Delta \mathrm{x}_{\mathrm{i2}}} = \text{Prob}(y_i = 1 \mid \bar{\mathbf{x}}'_{\mathbf{ij}}\boldsymbol{\beta}, x_{i2} + \Delta\mathrm{x}_{\mathrm{i2}}) - \text{Prob}(y_i = 1 \mid \bar{\mathbf{x}}'_{\mathbf{ij}}\boldsymbol{\beta})$$

$$= \frac{\exp(\beta_{01} + \beta_1 \bar{x}_{i1})}{\exp(\beta_{01} + \beta_1 \bar{x}_{i1}) + \exp(\beta_{02} + \beta_1[\bar{x}_{i2} + \Delta\mathrm{x}_{\mathrm{i2}}]) + \exp(\beta_{03} + \beta_1 \bar{x}_{i3}) + \exp(\beta_1 \bar{x}_{i4})}$$

$$- \frac{\exp(\beta_{01} + \beta_1 \breve{x}_{i1})}{\exp(\beta_{01} + \beta_1 \bar{x}_{i1}) + \exp(\beta_{02} + \beta_1 \bar{x}_{i2}) + \exp(\beta_{03} + \beta_1 \bar{x}_{i3}) + \exp(\beta_1 \bar{x}_{i4})},$$

where the bar over each price variable indicates that the price variables are evaluated at their mean values. This choice is arbitrary, though. Hence, we pick the initial value (i.e., the 2000 value) for all car models. Note also that Δx_{i2} is the amount by which the initial value of the price of S15 has changed. We pick $\Delta x_{i2} = 1$. With the price variable expressed in thousands of ringgit, $\Delta x_{i2} = 1$ is equivalent to RM1,000.