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# Transportation Research Part D

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## A dynamic marketing model for hybrid electric vehicles: A case study of Taiwan

Chaug-Ing Hsu <sup>a,\*</sup>, Hui-Chieh Li <sup>b</sup>, Shan-Mei Lu <sup>a</sup><sup>a</sup> Department of Transportation Technology and Management, National Chiao Tung University, Hsinchu 300, Taiwan, ROC<sup>b</sup> Tourism Management, Ta Hwa University of Science and Technology, Hsinchu County 307, Taiwan, ROC

### ARTICLE INFO

#### Keywords:

Hybrid electric vehicles  
Small world network  
Word of mouth

### ABSTRACT

This study uses an integrated model utilizing a small-world network and choice-based conjoint adoption model to examine the dynamics of consumer choice and diffusion in the hybrid electric vehicles market. It specifically compares the effectiveness of hybrid diffusion through the traditional word of mouth and via social media. The results show that without the advantage of increased gasoline prices, the growth of the hybrid vehicles market is insignificant, and that the Internet has a significant influence on the word of mouth effect in the purchasing process. Hybrid electric vehicles market shares decrease dramatically as a result of negative word of mouth communication via social media. The use of a higher fuel taxes is more effective than providing a subsidy for disposing of old vehicles and purchasing a hybrid.

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## 1. Introduction

The advantage of hybrid electric vehicles (HEVs) over conventional automobiles lies in their relatively lower environmental impact resulting from better fuel efficiency. There is a strong evidence of the rate of the adoption of HEVs and gasoline prices, the status given to different vehicles types, and the driving patterns and the socioeconomic features of potential buyers, but we know less about the impacts of official incentive policies. But beyond this we have, for example, little idea of how individuals obtain information about the relative attributes of HEVs, how they assess this information or how they pass it onto other. Here the focus is to learn more about the role of word of mouth (WOM) and other communications channels in the HEV market.

## 2. Dynamic choice model

In the study of the role of word of mouth's influence on car buying behavior, the consumer choice probability is described as a time-varying process based on the socioeconomic and spatial variables relevant to the dynamic characteristics exhibited. Specifically, the consumer's decision to adopt is the result of these variables at the time at the time of the decision, but what is relevant, and how, is influenced by prior WOM communications.

WOM effects are diffused via consumers' social networks. Each consumer, and the social relationship between consumers, is represented by a node and by links. A strong tie refers to the social relationship in which consumers frequently interact with each other, while a weak tie is less influential and generally involves less interaction. The significance of weak ties is that they are far more likely to be a bridge than strong ones, and more flexible; hence we follow Goldenberg et al. (2007), and

\* Corresponding author.

E-mail address: [cihsu@mail.nctu.edu.tw](mailto:cihsu@mail.nctu.edu.tw) (C.-I. Hsu).

treat them as random effects. For example, vehicle usage experiences and purchase information may be randomly generated via consumers occasionally chatting with a taxi driver, or to clients during regular interactions. Consumers can also receive product information via social media where one or more individuals with similar interests share reviews, often at a very rapid pace. A particular social media is denoted as a node where information from the social media that impacts on WOM is discussed.

An experienced consumer has already owned more than one vehicle, and his or her choice behavior differs from that of an inexperienced consumer because of this prior knowledge (Bettman and Park, 1980). We use an experienced consumer's utility function based on Roorda et al. (2009) where  $j$  and  $l$  denote a specific consumer and choice alternative. An experienced consumer can choose: to maintain the status quo; scrap an existing vehicle without replacement; sell an existing vehicle and replace it with a HEV, or with a gasoline vehicle; purchase an additional HEV or an additional gasoline vehicle; or scrap an existing vehicle with a replacement of HEV or gasoline vehicle. The utility  $U_{ij}^t$  of the experienced consumer  $l$  who chooses alternative  $j$  at time  $t$  can be:

$$U_{ij}^t = \alpha x_j^t + \beta y_i^t + \theta v_i^t + \gamma z_j^t + \delta w_{ij}^t + \varepsilon \quad (1)$$

where  $\alpha$ ,  $\beta$ ,  $\theta$ ,  $\gamma$  and  $\delta$  are the vectors of the parameters to be estimated;  $x_j^t$  is a vector of the characteristics of alternative  $j$  at time  $t$ ;  $y_i^t$  and  $v_i^t$  are vectors of socioeconomic variables and the vehicle fleet of experienced consumer  $i$  at time  $t$ ;  $z_j^t$  is a vector of government incentives with respect to alternative  $j$  at time  $t$ ;  $w_{ij}^t$  is the influence of WOM on buying alternative  $j$  on experienced consumer  $i$  at time  $t$ ; and  $\varepsilon$  is the error term. The "costs" associated with the current vehicle is seen in terms of vehicle utilization, increases in family size and vehicle maintenance costs. The alternatives for an inexperienced consumer are to purchase a HEV or a gasoline vehicle. The utility of inexperienced consumer  $l$  who chooses alternative  $k$  at time  $t$ ,  $U_{lk}^t$ , is thus

$$U_{lk}^t = \alpha' x_k^t + \beta' y_l^t + \gamma' z_k^t + \delta' w_{lk}^t + \varepsilon' \quad (2)$$

A WOM function is used to investigate the influences of social relationship, memory, negative and positive communications as well as the probability of having received information on consumer choice. Goldenberg et al. (2007) classify potential consumers into three categories; the positive who adopt the new product and can be expected to influence other potential consumers through future positive WOM; the disappointed who adopt the new product but are not satisfied, and thus potentially to negative WOM influences on potential consumers; and rejecters who are ex-potential adopters who received negative WOM and who may spread negative information to other potential consumers. There are also consumers who do not adopt the product but may still spread positive WOM influence on potential consumers, although here we classify consumers only as A, B, C or D corresponding to positive, ex-potential and positive consumers, disappointed consumers and rejecters. Thus, the WOM function,  $w_{ij}^t$  is thus

$$w_{ij}^t = R_p \cdot \left( P_s \cdot \frac{\sum_{t-m+1}^t Q_{ps}^t}{m} + P_w \cdot \frac{\sum_{t-m+1}^t Q_{pw}^t}{m} + P_i \cdot \frac{\sum_{t-m+1}^t Q_{pi}^t}{m} \right) - R_n \cdot \left( N_s \cdot \frac{\sum_{t-m+1}^t Q_{ns}^t}{m} + N_w \cdot \frac{\sum_{t-m+1}^t Q_{nw}^t}{m} + N_i \cdot \frac{\sum_{t-m+1}^t Q_{ni}^t}{m} \right) \quad (3)$$

where  $R_p$  and  $R_n$  are the probabilities of receiving positive and negative WOM,  $P_s$  and  $N_s$  are the influential levels of positive and negative information from strong ties,  $P_w$  and  $N_w$  are the influences of positive and negative information from weak ties,  $P_i$  and  $N_i$  are the influence levels of positive and negative information from social media,  $Q_{ps}^t$ ,  $Q_{pw}^t$  are the numbers of A and B consumers in the strong and weak tie networks,  $Q_{ns}^t$  and  $Q_{nw}^t$  are the number of C and D consumers in the strong and weak tie networks, and  $Q_{pi}^t$  and  $Q_{ni}^t$  are the number of users spreading information via social media. Following, Dodds and Watts (2005),  $m$  is the time that consumers retain memory of WOM information received from  $(t - m + 1)$  to  $t$ .

### 3. Questionnaire and results

Two questionnaires are used to illicit information on experienced and inexperienced consumers, and to obtained data regarding consumer characteristics and preferences in purchasing HEVs. The questionnaire consists of two sections. The first, asked questions related to responders' socioeconomic status such as age, gender, income, residence, vehicle possession and environment awareness. A quasi-stated preference experiment is also contained included asking respondents to choose from hypothetical choice sets. The choices are described by bundles of attributes values including gasoline price, acceleration performance,<sup>1</sup> vehicle prices and WOM influences. The second collected data for calibrating the parameters in the small-world network and the WOM function. The respondents are asked how many people, as well as the social relationships they discussed their choices before purchasing a vehicle. The respondents were also asked for what they thought was the level of influence exerted by various social relationships such as strong or weak ties and social media. The level of influence was measured on a five-point scale, ranging from extremely important, very important to unimportant with scores of 100, 75, 50, 25 and 0. Maximum likelihood estimation is used to estimate  $\hat{\alpha}$ ,  $\hat{\beta}$ ,  $\hat{\theta}$ ,  $\hat{\gamma}$  and  $\hat{\delta}$  in Eq. (1) and  $\hat{\alpha}'$ ,  $\hat{\beta}'$ ,  $\hat{\theta}'$ ,  $\hat{\gamma}'$  and  $\hat{\delta}'$  in Eq. (2).

<sup>1</sup> The time it takes to accelerate from zero to 100 km.

**Table 1**  
The parameters in the utility functions.

Variable type	Explanatory variable	Coefficient	
<i>Inexperienced consumers</i>			
Alternative specific constant	Purchase gasoline vehicle	3.8451 <sup>***</sup>	
	Generic variable	Vehicle Price –5.63E–06 <sup>***</sup>	
Alternative specific variable (HEV)	Acceleration performance	–1.45E–01 <sup>***</sup>	
	Gasoline price	1.13E–01 <sup>***</sup>	
	WOM effect	1.30E–03 <sup>***</sup>	
	Monthly income	1.23E–06 <sup>***</sup>	
	Environment awareness	4.39E–01 <sup>***</sup>	
	Residence	9.16E–01 <sup>***</sup>	
Goodness of fit statistics: $LL(0) = -401.3$ , $LL(c) = -383.5$ , $LL(\beta) = -331.4216$ , $\rho^2 = 0.1742$			
<i>Experienced consumers</i>			
Alternative specific constant	Stay in status quo	3.0678 <sup>***</sup>	
	Sell the used vehicle with a replacement of HEV	3.2548 <sup>***</sup>	
	Sell the used vehicle with a replacement of gasoline vehicle	1.2632	
	Additional purchase of HEV	1.00E–01	
	Additional purchase of gasoline vehicle	8.41E–01 <sup>*</sup>	
	Scrap the used vehicle with a replacement of HEV	–1.6729	
	Scrap the used vehicle with a replacement of gasoline vehicle	–9.71E–02	
	Alternative specific variable	Vehicle price	–2.40E–06 <sup>***</sup>
		Gasoline price	7.32E–02 <sup>***</sup>
		WOM effect	1.12E–03 <sup>***</sup>
Accumulated mileage		1.06E–05 <sup>***</sup>	
Alternative specific variable	Monthly income	5.86E–07 <sup>***</sup>	
	Vehicle price	–3.52E–06 <sup>***</sup>	
	Accumulated mileage	8.0E–06 <sup>***</sup>	
	Age of the original vehicle	6.2E–02 <sup>***</sup>	
Alternative specific variable	Monthly income	9.82E–07 <sup>***</sup>	
	WOM effect	1.03E–03 <sup>*</sup>	
Alternative specific variable	Age of the original vehicle	9.96E–02 <sup>*</sup>	
	Government subsidy	1.06332 <sup>*</sup>	
Alternative specific variable	Age of the original vehicle	1.78E–01 <sup>**</sup>	
	Goodness of fit statistics: $LL(0) = -1167.2800$ , $LL(c) = -861.3024$ , $LL(\beta) = -791.0511$ , $\rho^2 = 0.32231$		

<sup>\*</sup> Significant at the 10% level.

<sup>\*\*</sup> Significant at the 5% level.

<sup>\*\*\*</sup> Significant at the 1% level.

An Internet survey is used to collect the data, with e-mails for pre-notification to improve the response rate. The main disadvantage of an Internet survey is the possibility of getting a biased sample due to a decreased access rate to the Internet (Iragüen and Ortúzar, 2004), but in Taiwan it is over 70% of the population have Internet access (TWNIC, 2009). The survey was administrated for four weeks in February 2011.

The majority of the inexperienced respondents were under 30 years of age (65.3%),<sup>2</sup> with first-time vehicle buyers mainly from the younger consumer group. Most of the experienced respondents were young, highly educated consumers with a high income, and the major respondents with these characteristics are more likely to be attracted by low-pollution vehicles in line with the findings of Ewing and Sarigollu (1998).

Six and seven scenarios were presented giving 645 observations for inexperienced and 917 for experienced consumers. A binary logit model was calibrated for estimating the parameters in = equation 2, while a multi logit model was used for Eq. (1). The results are shown in Table 1.<sup>3</sup> As seen in the upper part relating to inexperienced customers, vehicle price and performance, consumer's monthly income, residence and environmental awareness, and gasoline price and the WOM effect are all significant, with the parameter signs consistent with other studies including Potoglou and Kanaroglou (2007), Erdem et al. (2010), and Axsen et al. (2009). Fuel efficiency and pollution emission are not listed in the upper part of Table 1 because they are not significant.

Turning to experienced consumers, the lower part of Table 1, vehicle price, monthly income, accumulated mileage and age of the present vehicle are significant in affecting the intention of trading in an existing vehicle for a new one; results in line with Brownstone et al. (2000) and Marell et al. (2004). Because gasoline is required for both new and used vehicles, its price is excluded from the model alternative as trading in an existing for a new gasoline vehicle. The impact of WOM on the purchase of HEVs is significant and positive as are government subsidies. Compared with several prior studies, variables such as fuel efficiency, performance, emissions and environmental awareness are not included in our model because of significance.

<sup>2</sup> Details can be found at <http://www.motc.gov.tw/ch/>.

<sup>3</sup> The *t*-statistics have been reduced  $(\sqrt{6})^{-1}$  and  $(\sqrt{7})^{-1}$  for the inexperienced and experienced consumers compared to the original values due to the repeated sampling from individual respondents using stated preference date (Wardman, 1988).

**Table 2**  
The influence of social relationships.

Social relationship	Information category	Influential level	
		Average	Median
Strong tie	Positive	58.63	50
	Negative	62.72	75
Weak tie	Positive	35.82	25
	Negative	40.50	50
Social media	Positive	53.66	50
	Negative	58.71	50

Table 2 shows the values of the level of influence of social relationships. The average and median of influential level of different social relationship are significantly different from each other by the assessment of *t*-test. Negative information is seen as more influential than positive information in all kinds of social relationships. Our survey also shows the average number of people involved in the discussions on vehicle purchase and usage experience is 3.4, while those occasionally ran into and chatted number 1.2.

#### 4. Case study

A case study is used to demonstrate the application of the model. It is assume that 80% of consumers in the market are experienced in according with the survey. The simulation has several stages

- Step 0: WOM's influence is initialized as zero. A database is created of consumer profiles including their average monthly income, vehicle possession, age of vehicle, accumulated mileage, WOM influence, environmental awareness and location of residence. Accumulated mileage, average monthly income and age of vehicle are randomly assigned to the node following the real data distribution in [Ministry of Transport and Communications \(2008\)](#). The assignment of environmental awareness and location of residence to a node is based on our survey.
- Step 1: At each time step *t*, consumer utility is estimated with respective to alternatives in which the utility gained by consumers can be calculated from equations 1 and 2. In addition to the consumer profile, the input data includes vehicle and gasoline prices. We assume that consumers are maximizing utility in their decision-making. If the optimal alternative is to maintain the status quo or scrap the present vehicle without replacement, the experienced consumer becomes a non-adopter. He or she is labeled a HEV/gasoline adopter if selling or scrapping the existing car and replaced it by a HEV or gasoline vehicle maximizes utility. Inexperienced consumers are labeled as HEVs/gasoline adopters if acquisition of a HEVs or gasoline leads to maximum utility.
- Step 2: Generate a social network based on the small world theory. Each node is connected to the nearest nodes with strong ties. Based on the survey, the number of weak ties is one with a randomly chosen probability between 0.01 and 0.1.<sup>4</sup> For a node with weak ties to others, we randomly generate a number between one and 20 as the length of the discussion.
- Step 3: Estimate of WOM influences are based on Eq. (3).
- Step 4. Update the database of the consumer profile, including a vehicle's accumulated mileage and age.
- Step 5: Proceed to the next time step  $t = t + 1$ . Inexperienced consumers who make their purchase decisions at time step *t* are randomly chosen with a probability of 0.1. Go to Step 2.

The model is verified by comparing the simulation results with data of the market share of the HEVs in the US. Taking Toyota as an example, the prices of gasoline vehicle and HEVs with engine over 1799 cc are \$16,360 and \$23,810; while those with engines over 3456 cc are \$30,955 and \$38,300 ([Toyota, 2011](#)). In the simulation, the price of the HEV is set to be 1.45 times that of a gasoline vehicle. Gasoline price data are taken from the US Energy Information Administration (EIA). In addition, a US government purchase subsidy ranging from \$500 to \$3000 per HEV is considered ([Gallagher and Muehlegger, 2011](#)). For simplification, we assume there are one weak and four strong ties, and the probability representing the randomness of the network is 0.05.

[Fig. 1](#) gives the simulation results set against the historical data of the market share of HEVs; differences in the estimated and the historical data are between 0.05% and 1.7%. The estimated market share of HEVs varies with the gasoline price as also shown in [Fig. 1](#). There was an increase in the market share of HEVs in 2009, at a time when consumers were being encouraged to scrap their existing vehicles if their consumption was 18 mpg or less as part of the US "Cash for Clunkers Program".

In looking at the impacts of government policies on the market for HEVs, we assume the socioeconomic characteristics of the consumers and their vehicles are distributed following the [Ministry of Transport and Communications \(2008\)](#) survey.

<sup>4</sup> The link-rewired probability  $p$  ( $0 < p < 1$ ) represents the randomness of the resulting small-world network and the dynamic properties of network structure ([Watts and Strogatz, 1998](#)). The network is most fitted to the characteristics of small-world network as ( $0.01 < p < 0.1$ ).

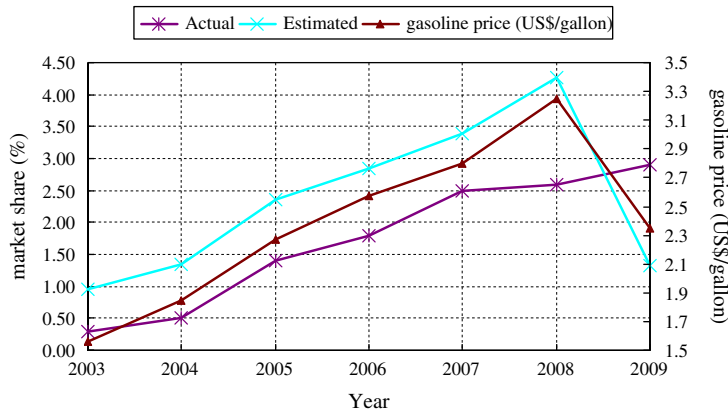


Fig. 1. Simulation results and historical data of the market share of HEVs in the US.

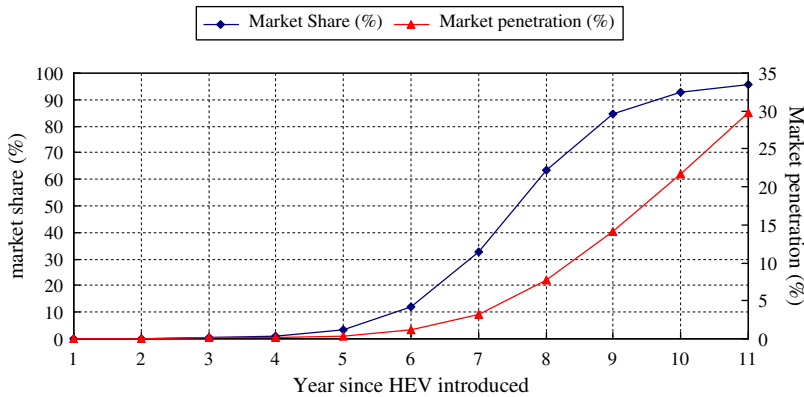


Fig. 2. Simulation results.

The gasoline price when HEVs enter the market is assumed to be NT\$30 per liter<sup>5</sup> in the first year, with an annual growth rate of 1.8% (Energy Information Administration, 2011). The price of a gasoline vehicle is taken as NT\$600,000, while that of a HEV is NT\$1.5 million with an annual decreasing rate of 9% (Axsen et al., 2009). There are assumed to be 6.65 million potential vehicle consumers in Taiwan.<sup>6</sup>

Fig. 2 shows the simulation results. The lower vehicle and higher gasoline prices result in a 95% of HEVs market share in the 10th year after HEVs are introduction. To examine the sensitivity of the results to trends in fuel and vehicle prices, two further scenarios applied. In the first it is assumed that the price of HEVs remains 1.56 times that of similar gasoline vehicle after the 5th year, and in the second, that in addition the gasoline price remains at NT\$32.8/liter after the 5th year without any further increases.

As shown in Fig. 3, market HEV share initially decreases to 30% and 9% in the first and second scenarios, suggesting that without a considerable rise in gasoline prices, the HEV market will shrink because their high capital cost. After maintaining the same level during the 5th and 6th years, the market share of HEVs increases even though there is no downward trending in their price, and this may be the result of WOM effects as well as the increase in gasoline prices. Fig. 4 examines the HEVs market share under various growth rate combinations for gasoline price and HEV price.

If HEVs are priced at over NT\$1.25 million (Fig. 4), the impact of increasing gasoline prices on the HEV market share is negligible. There are some effects at lower prices; e.g. if an HEV costs NT\$1.02 million, the HEV market shares are 3.4% and 8.0% when price of gasoline rises 1.8% and 3.6%, and 41.9% and 78.0% when the increases are 7.2% and 10%. These results are in line with Lave and MacLean (2002) finding that HEVs will have significant sales as fuel prices rise several-fold.

Turning to relationships between the HEV market share and the average accumulated mileage of a consumers' existing vehicles, Fig. 5 shows a quadratic specifications<sup>7</sup> when gasoline is priced at NT\$32.91/liter. The data refers to HEVs market

<sup>5</sup> NT\$100 = \$3.44 (January, 2013)

<sup>6</sup> To minimize the computing load, the study reduces the sample size at a rate of 10% at each trial and run simulations with different random seeds. After several trials, we found that the differences in HEVs market shares are small and the variations converged to an average value.

<sup>7</sup> This provides the best fit of a number of model forms examined.

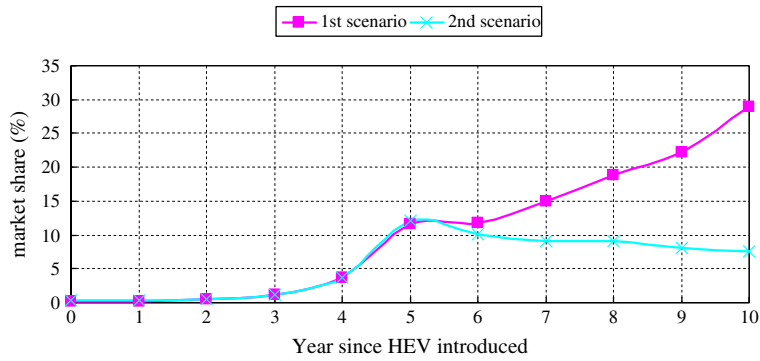


Fig. 3. Market share of HEVs under various scenarios.

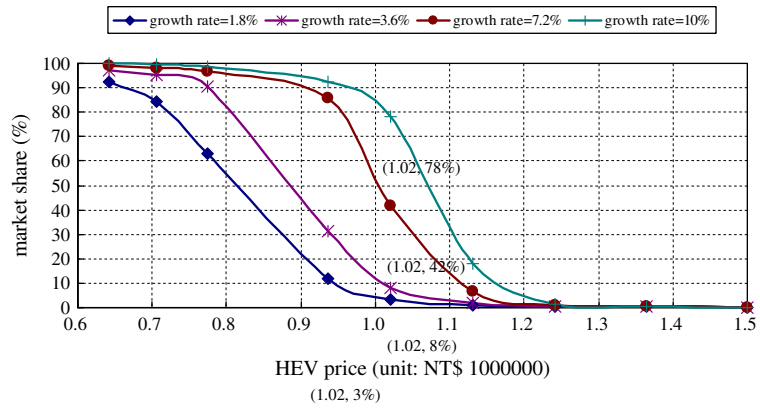


Fig. 4. HEVs market share under combinations of growth rates of gasoline and HEV prices.

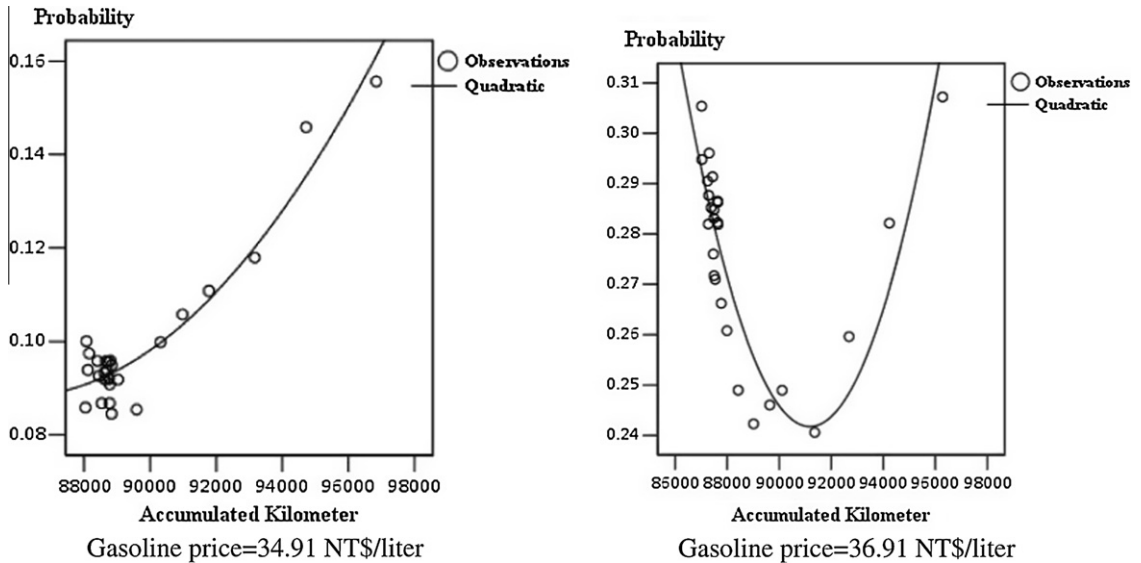


Fig. 5. Quadratic models results under various gasoline prices.

share after they have been available for 10 years, with  $x$ -axis referring to average accumulated kilometers of used vehicles in the market in the 10th year. The HEVs market share rises as the accumulated mileage traveled of the used vehicle increases. This relationship, however, becomes convex (right side of figure) if gasoline prices become NT\$36.91 per liter; high gasoline prices

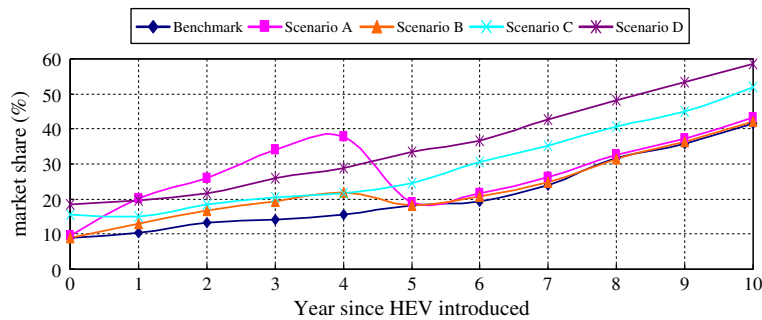


Fig. 6. Simulation results under different government subsidy policies.

lead to greater intentions regarding the purchasing of HEVs for both inexperienced and experienced consumers as shown in Table 2.

To assess the impact of government subsidies on promoting HEVs, we take a benchmark scenario that assumes an initial gasoline price of NT\$32.91/liter with an annual growth rate of 1.8%, with HEVs and gasoline vehicle priced at NT\$1 million and NT\$600,000. We consider four subsidy policies; Scenarios A and B assume a subsidy of NT\$100,000 for disposing of a vehicle nine years or older or with fuel consumption of 12.5 liter per 100 km or over, and replacing it with a HEV during the first four years after the latter has entered into the market. Scenarios C and D assume a fuel taxes of 3% and 5% dependent on vehicle usage.

As seen in Fig. 6, government subsidies in scenarios A and B promote the initial adoption of HEVs but their market share falls immediately to a normal level when the subsidies end. Although the policies under scenarios C and D result in a smaller market share during the first four years compared to scenarios A and B, the share continues to grow, with D shows emerging as the most effective promoter of HEV penetration. This follows Morrow et al. (2010) who concluded that fuel taxes generate the greatest reductions in CO<sub>2</sub> emission by increasing the cost of driving.

Considering the impact the Internet-WOM on HEV, if the market lacks these, the level of influence from strong and weak ties are 58.6 and 35.8. About 71% of new and used vehicle shoppers use the Internet to shop for vehicles and 33% of shoppers review the evaluations of specific types of vehicle from other shoppers (PolkView, 2011). Thus, the probability of receiving WOM through the Internet can be estimated as 0.234; i.e. for markets with Internet-WOM, the probability of receiving WOM through the Internet is 0.234 with an influence level of 53.66.

As depicted in Fig. 7, the HEV market share can be increased by 5–6% with Internet-WOM compared to the market share without Internet-WOM. The difference in market share is estimated to be 85 to 10% with further increases in gasoline prices. So far we have dealt with the positive WOM influence on the market share of HEVs, but there can also be negative implications. Three sceneries are investigated. First we assume a social network without negative WOM, and then two scenarios with negative WOM spreading via strong and weak ties and social media. Given the survey showed negative information is 1.34 times more influential than of positive information, we assume that 5% of adopters are dissatisfied with HEVs and spread negative information, with the remainder providing positive information.<sup>8</sup> In addition we assume that the probabilities for the adopters spreading positive and negative information are one and 0.12.

Fig. 8 shows that the market with negative WOM via social network is the one least influenced by WOM, suggesting that when there is negative WOM, social media has more influence in spreading negative information than social network. The diffusion of negative WOM leads a smaller market share. Since negative WOM via social networks is less influential, the difference in market shares between markets with and without negative WOM range between 1% and 6%, although HEVs share is decreased by about 25% due to the negative WOM via social media.

## 5. Conclusions

We formulated a dynamic marketing model and explored the market share and penetration of HEVs in Taiwan. When the price of gasoline rises, consumers are more concerned with the fuel cost savings associated with HEVs and less with the increased price of the HEV, resulting in an increased HEV market share. However, the impact of gasoline price on the HEV market becomes negligible if the HEV is priced beyond an acceptable level. The evidence indicates that Internet-WOM increases the market share of HEVs, but when there is negative WOM, the Internet is more influential media than social networking in spreading negative information. The implementation of additional fuel taxes is more effective for promoting HEVs than providing a subsidy for disposing of old vehicles when purchasing a HEV. However, the government in Taiwan should pay attention to any public backlash when implementing a fuel tax policy.

<sup>8</sup> East et al. (2007) found the frequency of receiving positive WOM is 8.2 times that of negative WOM.

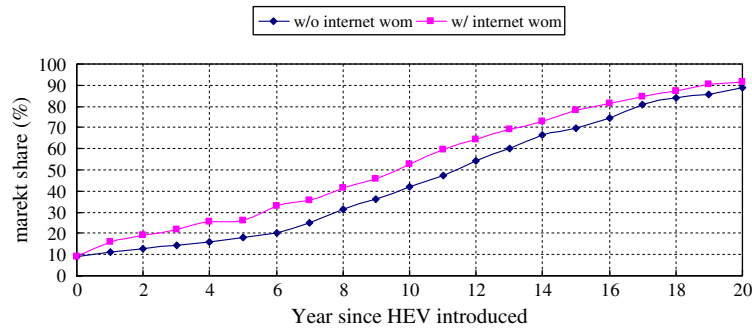


Fig. 7. Simulation results with and without Internet-WOM.

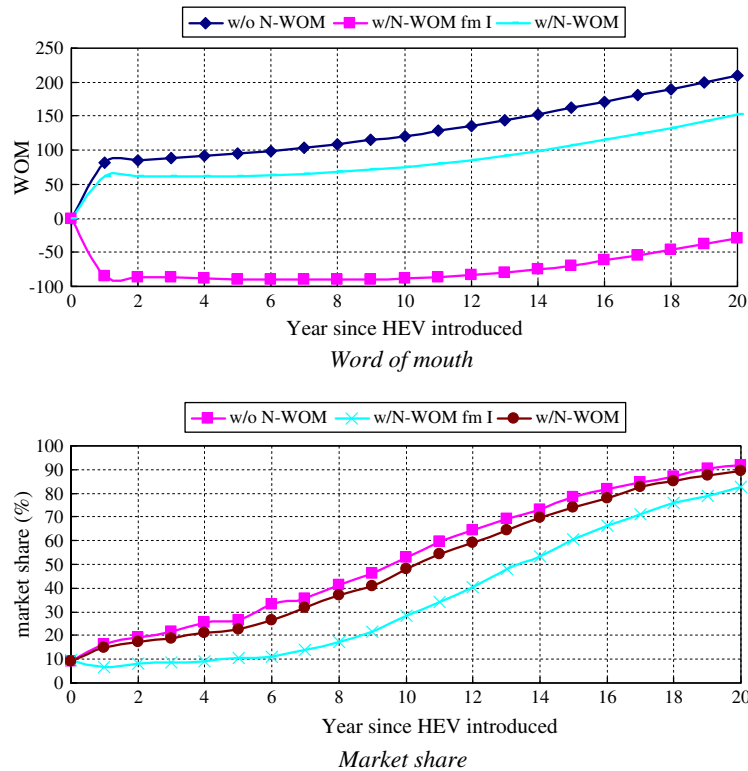


Fig. 8. Simulation results with and without negative word of mouth.

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