

Article

Is an Incentive Policy for Energy Efficient Products Effective for Air Purifiers? The Case of South Korea

Woojae Kim ¹, Sungmin Ko ¹, Myoungjin Oh ¹, Ie-jung Choi ² and Jungwoo Shin ^{1,*}

¹ Department of Industrial and Management Systems Engineering, Kyung Hee University, 1732 Deogyong-daero, Giheung-gu, Yongin, Gyeonggi 17104, Korea; woojaekim@khu.ac.kr (W.K.); sungmine03@khu.ac.kr (S.K.); bristo94@khu.ac.kr (M.O.)

² R&D Financial Project Evaluation Center, Science and Technology Policy Institute (STEP), A-3F Sejong National Research Complex, 370 Sicheong-daero, Sejong-si 30147, Korea; matthew@stepi.re.kr

* Correspondence: shinjung11@khu.ac.kr; Tel.: +82-31-201-3687; Fax: +82-31-204-8114

Received: 15 March 2019; Accepted: 28 April 2019; Published: 1 May 2019



Abstract: Recent increases in fine and ultrafine dust in South Korea have led to sharp increases in the sale of air purifiers, and that trend is expected to continue. As the sale of air purifiers increases, the energy that is consumed by air purifiers also increases. Therefore, improving the energy efficiency of air purifiers is an important part of improving the overall energy efficiency of society. We studied how different incentive policies affect consumer behavior because encouraging people to buy energy efficient air purifiers is important. We first investigated consumer preferences regarding air purifiers. Stated preference data were gathered from a choice experiment and a mixed logit model was used for the analysis. The results show that the most preferred attribute was price, followed by an eco-label. Based on that result, we conducted a scenario analysis to examine the economic and environmental effects of an incentive policy and eco-labeling. The monetary incentive policy increased the market share for air purifiers with a first-grade energy efficiency rating to 2.2%. The annual electricity use reduction was 5.9 GWh, with a CO₂ emission reduction of 2520 tons and a policy monetary benefit of KRW 441,340,922 when we converted the effect of that market share change into economic and environmental terms. Eco-labeling also brought considerable change in the market share. These results provide a reference for implementing policies to encourage consumers to purchase energy efficient air purifiers.

Keywords: air purifier; energy efficiency; eco-label; incentive policy; choice experiment; hedonic pricing; greenwashing

1. Introduction

As economic growth occurs worldwide, energy demand has continuously increased, causing serious problems, such as global warming, air pollution, and ozone destruction. Therefore, improving energy efficiency, which is cost effective and has no negative social effects, has become important [1]. Energy efficiency can be improved on both the supply and demand sides. On the supply side, suppliers or generators can improve the efficiency of energy production and, on the final demand side, consumers can use energy efficient instruments. The laws of thermodynamics and physics limit improvements to energy efficiency on the supply side [1]. Therefore, using generated energy efficiently on the consumer side is necessary. Specifically, in the residential sector, the use of energy efficient appliances is important because the energy that is consumed by appliances has increased 58% since 2000 [2].

Recently, in South Korea, fine and ultrafine dust has become a serious national problem. The number of pm 2.5 ultrafine warnings between 1 January and 1 April increased by 3.4 times, from 51 in 2016 to 160 in 2018. Since 1 January 2019, the number of warnings has already exceeded

200 [3]. The concentration of ultrafine dust is also very high, at 25.1 ppm, which is more than twice the organization for economic cooperation and development (OECD) average of 12.5 ppm [4]. As a result, air purifier sales have dramatically increased, from 0.8 million units in 2015 to about 2 million units in 2018, making them a KRW 1.4 trillion (USD 1 = KRW 1125.50) market [5] that is expected to continue growing. Increased sales of air purifiers have resulted in an increase in the amount of energy that is used by air purifiers, which has made the minimization of that increased energy use through the use of energy efficient air purifiers very important.

Therefore, the government should implement policies to encourage people to buy energy efficient air purifiers. Policies that could encourage consumers to buy energy efficient appliances include direct incentive policies, energy-labeling policies, and eco-labeling. A direct incentive policy financially supports consumers when they purchase an energy efficient appliance. An energy-labeling policy labels products with energy efficiency ratings and energy consumption data. Eco-labeling identifies the products that require minimal energy and resources and that generate minimal greenhouse gases and pollutants. Previous studies have demonstrated that direct incentive policies, energy-labeling policies, and eco-labeling all affect energy usage [6–13]. However, such policies only succeed in increasing energy efficiency if people buy energy efficient appliances. Therefore, it is important to analyze which attributes consumers most prefer when they are shopping for air purifiers, because that information will make it possible to encourage people to purchase energy efficient air purifiers.

A choice experiment (CE) is commonly used to analyze consumer preferences regarding appliance attributes. Lee et al. [14] studied the effect of screen size on the purchase of televisions and found that people prefer to purchase TVs with smaller screens rather than larger screens. Waechter et al. [15] studied the effects of energy-labeling on the purchase of televisions and refrigerators and found that energy-labeling had rather low effects on consumer purchases. Zhou and Bukenya [16] studied how much energy-labeling affects the purchase of air conditioners and found that consumers preferred higher energy grades. Ward et al. [17] considered whether being made in a manufacturing factory that is a green power partner affected the purchase of air conditioners. Consumers were willing to pay \$48.52 to \$70.95 more for a refrigerator that was made by a green power partner. However, few studies have analyzed the effects of incentive policies regarding the purchase of energy efficient air purifiers or performed a cost-benefit analysis of such an incentive policy. Other policies that could affect the purchase of air purifiers should also be considered.

We collected stated preference data using a survey and analyzed those data with the CE method to fill that research gap. We estimated consumer preferences for price, filter grade, coverage, power consumption, eco-labeling, and CA (Clean air)-labeling, and we quantified those consumer preferences with the marginal willingness-to-pay (MWTP) for each attribute. A mixed logit model that was based on Bayesian estimation was used as the estimation model. Taking the results of that analysis, we next considered whether a particular direct incentive policy would encourage consumers to buy an energy efficient air purifier and then conducted a cost-benefit analysis of that incentive policy. We also analyzed the effects of eco-labeling on the purchase of energy efficient air purifiers.

The rest of this study is organized, as follows. In Section 2, we summarize previous studies of energy-labeling, incentive policies, and eco-labeling. In Section 3, we describe our mixed logit model and the Bayesian estimation method. In Section 4, we describe how we designed our survey instrument. The description includes the CE attributes and attribute levels, an example choice set, and the demographic properties of the survey respondents. In Section 5, we discuss our results and use hedonic pricing to simulate the effects of a direct incentive policy and eco-labeling on the purchase of energy efficient air purifiers. In the conclusion, we summarize our results, discuss this study's limitations, and explain the policy implications of our findings.

2. Background

Energy-labeling provides information regarding the energy efficiency and energy consumption of household appliances and effectively communicates energy usage information to consumers.

Energy-labeling has been shown to affect the decision-making process when people are selecting products [18,19], and the implementation of an energy-labeling policy plays an important role in the diffusion of energy-efficient products [20]. Many countries have mandated energy-labeling for household electrical appliances to improve the efficiency of household power consumption [21]. People want information that will allow them to lower their energy costs and improve the environment, and they are willing to pay extra money to get that information [17].

Energy-labeling of household appliances not only helps to reduce electricity consumption at home, but it also benefits society by improving the environment. Households tend to reduce their energy use when information regarding energy consumption is provided, reducing household electricity consumption by about 2% [22,23]. Energy-labeling also helps to lower peak power demand by reducing the power consumption of appliances [24]. On the environmental side, energy-labeling can help to reduce greenhouse gas emissions, particularly in countries that heavily rely on fossil fuels for power generation [25].

Several factors that affect the diffusion of energy-efficient household appliances influence energy-labeling. For instance, consumer awareness of energy-labeling and pro-environmental attitudes affects personal norms through individual responsibility, which encourages the purchase of energy-efficient, environmentally friendly products [26–28]. Moreover, consumer preferences tend to improve when energy-consumption information is effectively communicated through well-designed energy labels [28–30]. Providing consumers with direct incentives to purchase energy-efficient products also positively affects the market share of such products [31]. Incentives can help early-stage products to mature in the marketplace and encourage private investment [32]. Consequently, providing incentives for energy-labeling accelerates the diffusion of energy-efficient products into the marketplace, thereby increasing the effects of energy-labeling policies [9]. Therefore, the government often uses incentive policies to encourage consumers to invest in energy efficient products, and an incentive program has been developed to ensure that such products are rapidly introduced into the market [8].

Korean people have become interested in air purifiers, whose sales volume is increasing due to environmental problems. Growth in the air purifier market is closely linked to energy consumption, and policies, such as energy-labeling, could help reduce energy consumption by promoting the sale of energy-efficient air purifiers [33]. However, the policy might not have a significant effect on consumer decisions to purchase energy efficient appliances [27,34], so both the costs and benefits of any policy should be considered before implementation [9]. Therefore, here, we analyze the cost and benefits of energy-labeling incentives by using hypothetical scenarios to prepare for the increase in electric power consumption that is already being caused by the increase in air purifier use.

In addition to energy-labeling, air purifiers that are sold in Korea have eco-labeling that certifies environmentally friendly products that offer low carbon emissions from production to disposal. Consumers prefer pro-environmental products when they are deciding to purchase products [35]. However, when consumers think that the pro-environmental information on products is exaggerated [36], they consider it *greenwashing*. People stop trusting the pro-environmental information that companies provide as the perception of greenwashing increases [37–39]. People's mistrust causes confusion and eventually results in a reduction in the quality of pro-environmental products [40]. The effects of greenwashing mean that pro-environmental information can lead consumers to hold off on their purchases of pro-environmental products [37,39,41].

Therefore, here, we consider the effects of both a direct incentive policy and eco-labeling on Korean consumers' air purifier selection. We also analyze the costs and benefits of those incentives in terms of market share change. In general, previous studies have focused on how much labeling and incentive policies affect consumer purchases. In this study, instead, we use simulations to identify the policy effects in terms of market share change, and we analyze the positive effects of those market share changes in terms of electricity use and greenhouse emissions.

3. Methodology

3.1. Discrete Choice Model

We used discrete choice models to analyze consumer preferences for core factors when purchasing air purifiers, such as price, filter grade, power consumption, and eco-labeling. According to Hess et al. [42], several choice paradigms can be applied in choice modeling, including random utility maximization models, random regret minimization models, and elimination by aspects models. Random utility maximization models are the most commonly used among those choice paradigms. Those models assume that consumers choose a product that maximizes their utility and where consumer heterogeneity exists. We used a mixed logit model to analyze consumer preferences regarding air purifiers in South Korea. The mixed logit model overcomes the multinomial logit model's limitations by incorporating respondent heterogeneity and relaxing the independence from irrelevant alternatives. The utility for alternative j selected by consumer n in choice situation t based on the random utility model is expressed as Equation (1) [43,44]:

$$U_{njt} = V_{njt} + \varepsilon_{njt} = \beta' x_{njt} + \varepsilon_{njt} \quad (1)$$

where the component of this expression is composed of a determinant part V_{nj} and a stochastic part ε_{nj} . x_{njt} is a vector that represents consumer n 's observable attributes for alternative j in choice situation t . β' is a preference parameter that represents the corresponding attribute. The stochastic part is a random error term that represents unobservable influences. The probability that consumer n chooses alternative j in choice situation t is defined as Equation (2) [44]:

$$P_{njt} = \int \frac{\exp(V_{njt})}{\sum_m \exp(V_{nkt})} f(\beta) d\beta. \quad (2)$$

We estimate the mixed logit model through the Bayesian estimation method, which can flexibly cope with problems, such as the complexity of expressions and the local optimal solution that occur while estimating the likelihood function. We calculated the MWTP and relative importance (RI) to derive a comparable meaning through the estimated β . MWTP indicates the amount respondents are willing to pay to maintain their utility when the level of an attribute changes by one unit, and it can be calculated by dividing each attribute parameter by the price parameter, as shown in Equation (3). RI represents how much each attribute or alternative influences the situation in which the respondents chose an alternative. Multiplying the estimated coefficient by the part-worth calculates its value, which is an interval of the attribute level, as shown in Equation (4).

$$MWTP_n = -\frac{\beta_n}{\beta_{price}} \quad (3)$$

$$RI_n = \frac{part - worth_n}{\sum_n part - worth_n} \times 100 \quad (4)$$

3.2. Hedonic Pricing

Rosen first introduced the hedonic pricing method in 1974, and Freeman summarized it in 1979. Hedonic pricing is used when analyzing which attributes affect prices and how much each attribute affects the price. Therefore, hedonic pricing is used in many areas, such as housing [45], tourism [46], and appliances [47]. Equation (5) shows the equation for the hedonic pricing method.

$$P(H) = f(C_1, C_2, \dots, C_k) \quad (5)$$

$P(H)$ is the vector price of a product and C_k is an attribute of that product. Each point of the price in $P(H)$ is determined by a set of C_k [45]. Computing this equation at each point with a regression analysis makes it possible to derive a coefficient for each attribute. The significance of the coefficients indicates whether an attribute is a core factor of pricing. Furthermore, the value of an attribute's coefficients implies the marginal price of that attribute.

4. Survey Design

The survey for this study was conducted online in July 2018 by a professional survey company (Gallup Korea). A total of 304 respondents in South Korea between the ages 20 and 60 completed our questionnaire. Householders and their spouses participated in the survey. The respondents were selected to approximate the gender and age distributions of the population in Korea. Table 1 provides the demographic properties of the survey respondents.

Table 1. Demographic properties of the sample.

Category	Detail	Respondents	Percentage (%)	General Population ¹
Total		304	100	51,446,000
Sex	Male	153	50.3	50.1
	Female	151	49.7	49.9
Age	20–29	41	13.5	10.0
	30–39	106	34.9	23.3
	40–49	110	36.2	32.5
	50–59	47	15.5	34.2 ²
Income (KRW 10,000) ³	<300	103	33.9	
	300–399	59	19.4	-
	400–499	48	15.8	
	>500	94	30.9	
Education	Under high school	2	0.65	
	High school	17	5.6	
	University/college	228	75	-
	Graduate school	57	18.75	

Note: ¹ The Korean Statistical Information Service (<http://kosis.kr/eng>) provides information about the general population of Korea. To compare with the survey data, we extracted information about the heads of households and their spouses. ² Because the survey was conducted online, respondents older than 50 had a low response rate.

³ Average monthly income in 2016 was KRW 4.4 million per household.

In a conjoint analysis, it is possible to know how much respondents prefer one attribute when compared with others [48]. For this reason, CEs are often used to analyze consumer preferences for appliances. Using attributes and attribute levels to create alternatives, one can create choice sets for respondents, who then choose what they prefer [49]. When selecting attributes, it is important that they be essential to the product to provide circumstances that are similar to those in the real market [50].

For this study, we chose residential air purifiers as the target product. As the core attributes, we chose price, filter grade, coverage, power consumption, eco-labeling as certified by the government, and CA-labeling as certified by the Korean air cleaning association (an industry organization). Price is a main attribute that affects consumer choice, so many previous studies of consumer preferences for appliances have included price as an attribute [15,51–54]. Filter grade is included, because people who generally value clean air want to buy a purifier that filters as many pollutants as possible [55], which makes it an attribute that affects consumer purchases. Coverage and power consumption are included to consider the air purifier's performance and energy consumption. Additionally, these attributes can be used to infer the energy efficiency rating [56]. Other studies have similarly included energy efficiency and energy efficiency rating as attributes [16,51,52,57]. The eco-label tells consumers whether the government has certified that the air purifier minimizes the need for energy and resources and the generation of greenhouse gases and pollutants [58]. In a similar way, the CA-label tells consumers

whether the Korean air cleaning association has certified an air purifier. Although the CA-label was not considered to be an attribute in previous studies, we included it, because we expected it to be an important factor that affects people's purchases. Previous studies included brand as an attribute. We do not include brand, because that is not the focus of this study. Table 2 lists the attributes and their corresponding levels.

Table 2. Air purifier attributes and attribute levels.

Attribute	Description	Level
Price (KRW10,000)	Price	10/25/50/100
Filter grade	E11 grade filter	E11/H13/U15
	- Dust elimination ratio: 95% ratio	
	- Filterable dust particle size: > 0.5 μm	
H13 grade filter	H13 grade filter	
	- Dust elimination ratio: 99.95% ratio	
	- Filterable dust particle size: >0.3 μm	
U15 grade filter	U15 grade filter	
	- Dust elimination ratio: 99.995% ratio	
	- Filterable dust particle size: >0.3 μm	
Coverage (m^2)	Area appliance can purify (encouraged adequate area is 130% of living area)	17/33/66/100
Power consumption (W)	Amount of electricity used per second	10/30/50/75
Eco-label	Government certified as eco-friendly	No eco-label/eco-label
CA-label	Industry certified performance	No CA-label/CA-label

All of the attributes and attribute levels create a total of 768 ($4 \times 3 \times 4 \times 4 \times 2 \times 2 = 768$) alternatives, which is too many to offer to respondents. Simply reducing alternatives for statistical efficiency can create a dominant option, which causes an inefficiency of design. Therefore, alternatives have to be reduced while using a fractional factorial design that considers both the statistical efficiency and design efficiency [47]. In this study, we used fractional factorial design to reduce the original 768 alternatives to 16 alternatives, which we divided into four choice sets. We carefully considered the arrangement of alternatives to prevent a dominant alternative from occurring. Table 3 provides an example choice set.

Table 3. Example choice set.

Attribute	Type A	Type B	Type C	Type D
Price (KRW)	1,000,000	1,000,000	500,000	500,000
Filter grade (removal efficiency %)	E11 (95%)	H13 (99.95%)	E11 (95%)	E11 (95%)
Coverage (m^2)	17	66	33	66
Power consumption (W)	75	50	30	75
Eco-label	Eco-label	No eco-label	No eco-label	Eco-label
CA-label	CA-label	No CA-label	No CA-label	No CA-label
Most preferred type	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

5. Results and Discussion

5.1. Model Estimation

Equation (6) provides the equation used to estimate the random utility function for respondent j in the mixed logit model.

$$U_{nj} = \beta_1 X_{pri} + \beta_2 X_{fil} + \beta_3 X_{cov} + \beta_4 X_{con} + \beta_5 D_{eco} + \beta_6 D_{CA} + \varepsilon_{nj} \quad (6)$$

Here, X_{pri} , X_{fil} , X_{cov} , and X_{con} are continuous variables, and D_{eco} and D_{CA} are the dummy variables. X_{pri} represents the price, with a high value of X_{pri} meaning that the product is expensive. X_{fil} is the filter grade, with a high value of X_{fil} meaning that the product can filter smaller sizes of fine dust. X_{cov} and X_{con} represent coverage and power consumption, respectively, with higher values indicating that the coverage and power consumption are larger. D_{eco} (=0 or 1) represents eco-labeling, with a value of 0 indicating no eco-label and 1 indicating an eco-label. Similarly, D_{CA} (=0 or 1) represents the CA-label, with 0 indicating no CA-label and 1 indicating a CA-label. All of the variables are assumed to have a normal distribution.

In this study, we used the Bayesian method to estimate the mixed logit model. We drew 20,000 samples and burned in 10,000 samples to eliminate the starting point effects. Our estimations were performed using the remaining 10,000 samples. Price, coverage, and eco-label were significant at 1% in the results, and the rest of the attributes were significant at 5%. We analyzed MWTP and RI to quantify those results with monetary units. Table 4 shows the estimation results.

Table 4. Estimation result of mixed logit model.

Attribute	Assumed Distribution	Mean of β	Std. err.	$P > t $	MWTP (KRW)	RI
Price (KRW)	Normal	−0.19948 ***	0.02757 ***	0.000	-	32.5%
Filter grade	Normal	4.18264 ***	0.63493 **	0.000	20,762	3.8%
Coverage (m ²)	Normal	0.16636 **	0.07739 ***	0.032	8,440	7.4%
Power consumption (W)	Normal	−2.09244 ***	0.34048 **	0.000	−10,438	24.6%
Eco-label	Normal	1.50229 ***	0.15072 ***	0.000	753,277	27.5%
CA-label	Normal	0.20861	0.22109 **	0.345	99,923	4.2%

Note: *** Significant at the 1% level; ** Significant at the 5% level.

As shown in Table 4, the coefficients for price and power consumption are negative, and those for the rest of the variables are positive. A negative coefficient means that consumers prefer that attribute to have a smaller value. In other words, consumers prefer prices to be cheaper and the power consumption to be lower. Low power consumption means lower power costs, which is generally consistent with the preference for low prices. In contrast, the coefficients for coverage and eco-label are positive, indicating that consumers prefer air purifiers with larger coverage areas and eco-labels.

MWTP indicates the willingness to pay for a one-unit change. In the filter grade, consumers are willing to pay KRW 20,762 for an air purifier with a higher rating. In coverage, consumers are willing to pay KRW 8440 for an air purifier with a 1 m² increase in area being covered. In power consumption, consumers are willing to accept a power consumption increase of 1 W if they can pay KRW 10,438 less. Consumers are willing to pay KRW 753,277 more for an air purifier with an eco-label.

As for RI calculations, the order was price, eco-label, power consumption, coverage, and filter grade. The RI of the CA-label attribute was relatively low when compared with the other attributes. As the value consumers place on pro-environmental products that are certified by the government has become higher, enterprises have started labeling their products with their own pro-environmental and performance certifications. The increased number of labels has caused confusion (called greenwashing) among consumers, who cannot always distinguish the official eco-label certification by the government from private labels. Some people are even willing to pay more money for private labels than for official

labels [36]. However, the coefficient for the CA-label is insignificant as shown in Table 4. In other words, respondents indicated that the CA-label does not affect their willingness to pay for an air purifier, which means that greenwashing has not happened in air purifier labeling.

5.2. Scenario Analysis

In July 2016, the South Korean government tried to implement an incentive policy to support 10% of the price of appliances with a first-grade energy efficiency rating. However, the government failed to raise sufficient funds for that program and announced that it would pay for products that were only purchased at certain stores. That announcement caused much controversy, and so the program did not go into effect. Therefore, in this study, we conducted scenario analyses to simulate the incentive policy as originally planned and then analyze whether it could encourage consumers to buy an air purifier with a first-grade efficiency rating.

We first collected price, filter grade, energy efficiency rating, CA-labeling, and coverage data for air purifiers in the market to run the simulation. Subsequently, we set price as a dependent variable and filter grade, energy efficiency rating, CA-labeling, and coverage as independent variables. Next, while using the hedonic pricing method, we estimated the effects of each variable on price, and then we simulated the effects of a 10% incentive policy on market share.

To collect data regarding air purifiers in the market, we used the online commercial shopping mall Danawa (www.danawa.com). We collected data on 137 air purifiers in February 2019. Equation (7) provides the regression equation that we used to conduct the hedonic pricing analysis. β_1 is the coefficient of the filter grade, β_2 is the coefficient of the energy efficiency rating, β_3 is the coefficient of the CA-label, and β_4 is the coefficient of coverage.

$$Y = \alpha + \beta_1 X_{fil} + \beta_2 X_{eff} + \beta_3 D_{CA} + \beta_4 X_{cov} \tag{7}$$

In regression analysis (Table 5), the filter grade is significant at the 10% level, energy efficiency rating and CA-labeling are significant at the 5% level, and coverage is significant at the 1% level. Except for the energy efficiency rating, all of the variables have a positive relationship with price; in other words, having a high filter grade, CA-label, and large coverage all make an air purifier more expensive. In contrast, energy efficiency has a negative relationship with price; an air purifier with an energy efficiency rating that is close to 1 (the best grade) is more expensive than one with a higher energy grade. The result for CA-label is intriguing among those variables. CA-label is not significant in the respondents' preferences, which means that consumers are not willing to pay more money for an air purifier with a CA-label than for one without it, as shown in the results in Table 4. However, when enterprises set the price of an air purifier, the CA-label had the largest effect among the variables tested. When consumers buy an air purifier that has the performance that they need and a CA-label they does not need, the price of the CA-label could already be reflected in the price. Therefore, consumers should pay attention to product labels to ensure that they buy an air purifier with the certification that they want.

Table 5. Estimation results from hedonic pricing analysis.

Parameter	Coefficient	Standard Error	t-Value	P > t
α	112,929	97,499	1.158	0.2488
β_1	28,497 *	16,631	1.713	0.0890
β_2	-42,805 **	21,208	-2.018	0.0456
β_3	58,566 **	31,972	2.582	0.0109
β_4	6184 ***	1053	5.871	3.33×10^{-8}
Observation	137	Log likelihood		-1851.933

Note: *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

Using data that were collected from the real market, we calculated the average for each variable to set the initial market share. The averages were: filter grade E12, energy efficiency rating 2.3, coverage of 51 m², and no CA-label. Thus, the initial market was set for an air purifier with 99.5% dust removal efficiency, an average energy efficiency rating in the second-grade, 15 pyung (Pyung is a unit of South Korean housing that is about 3.3 m²) of coverage, and no eco-label or CA-label. The air purifier had no eco-label because only two air purifiers available in South Korea have an eco-label, and it had no CA-label because the CA-label was insignificant in the consumer preference analysis. The coverage was fixed at 15 pyung, and the power consumption was varied to affect the energy efficiency grade (because the energy efficiency rating can be inferred from the power consumption and coverage) [49]. The price gap between energy efficiency ratings was KRW 40,000, so we set the price of each air purifiers. Table 6 presents the market share results for air purifiers that were created by this process.

Table 6. Initial market share for air purifiers.

Attribute	1st-Grade	2nd-Grade	3rd-Grade	4th-Grade	5th-Grade
Price (KRW 100,000)	4.4	4	3.6	3.2	2.8
Filter grade	0.995	0.995	0.995	0.995	0.995
Coverage (15 pyung)	1.5	1.5	1.5	1.5	1.5
Power consumption (100 W)	0.24	0.48	0.72	0.96	1.2
Eco-label	0	0	0	0	0
CA-label	0	0	0	0	0
Market share	38.4%	22.4%	15.4%	12.4%	11.5%

Table 7 shows the market share change toward first-grade energy efficiency rating air purifiers caused by various incentive proportions.

Table 7. Change in market share by incentive policy.

Incentive Price (Incentive Proportion %)	Market Share				
	1st-Grade	2nd-Grade	3rd-Grade	4th-Grade	5th-Grade
Base	38.4%	22.4%	15.4%	12.4%	11.5%
KRW 8800 (2%)	38.8%	22.2%	15.3%	12.3%	11.4%
KRW 17,600 (4%)	39.2%	22.0%	15.2%	12.2%	11.4%
KRW 26,400 (6%)	39.7%	21.8%	15.1%	12.1%	11.3%
KRW 35,200 (8%)	40.1%	21.6%	14.9%	12.0%	11.3%
KRW 44,000 (10%)	40.6%	21.4%	14.8%	12.0%	11.2%
KRW 52,800 (12%)	41.1%	21.3%	14.7%	11.9%	11.1%
KRW 61,600 (14%)	41.5%	21.1%	14.6%	11.8%	11.0%
KRW 70,400 (16%)	42.0%	20.9%	14.5%	11.7%	11.0%
KRW 79,200 (18%)	42.4%	20.7%	14.3%	11.6%	10.9%
KRW 88,000 (20%)	42.9%	20.5%	14.2%	11.5%	10.8%

The simulation results show that the incentive policy effectively encourages people to buy energy efficient air purifiers [9]. In the simulation, the market share of the first-grade energy efficiency air purifiers increased by 4.5% when 20% of the price of a first-grade energy efficiency air purifier was given as an incentive. The market share of first-grade energy efficiency air purifiers increased by 2.2% when 10% of the price of a first-grade energy efficiency air purifier was given as an incentive (as originally planned in the South Korean policy).

Subsequently, we analyzed whether the change in market share from a 10% incentive was cost effective by considering the annual appliance usage time [59], average time of air purifier usage (h/day) [56], CO₂ emissions (g/h) [56], price of electricity (KRW/kWh) [60], and price of CO₂ emissions (KRW/ton) [61]. We found that the change in market share driven by a 10% incentive policy reduced the annual electricity usage by about 5.9 GWh and annual CO₂ emissions by about 2520 t. Therefore,

the total reduction in electricity usage is about 39.66 GWh and the total reduction in CO₂ emissions is about 16,857 t, given that household appliances are generally used for 6.69 years [59] before they are replaced. An annual gain of KRW 441,340,922 could be obtained through the incentive policy when those effects are converted into monetary units as a benefit by multiplying them by the price of electricity and CO₂ emissions, with the 10% price incentive being counted as the cost [32].

Next, we considered what else could affect market share. We simulated the market change when only first-grade energy efficiency air purifiers had an eco-label, when only second-grade energy efficiency air purifiers had an eco-label, and when both first- and second-grade energy efficiency air purifiers had an eco-label to estimate the effects of eco-labeling as an alternative. Table 8 provides the results of those simulations.

Table 8. Change in market share caused by eco-label changes.

Attribute	Market Share				
	1st-Grade	2nd-Grade	3rd-Grade	4th-Grade	5th-Grade
Base	38.4%	22.4%	15.4%	12.4%	11.5%
1st/Eco	64.3%	14.9%	8.8%	6.4%	5.5%
2nd/Eco	26.8%	52.9%	8.7%	6.3%	5.4%
1st, 2nd/Eco	47.8%	32.2%	9.2%	6.0%	4.8%

In this simulation, when the air purifiers had an eco-label, consumer purchasing increased in every case. When only first-grade energy efficiency air purifiers had an eco-label, their market share increased by about 26%. When only second-grade energy efficiency air purifiers had an eco-label, their market share increased by about 30%. When both first- and second-grade energy efficiency air purifiers had an eco-label, the market share of the two grades together reached 80%.

6. Conclusions

Environmental pollution and the negative effects of increasing energy consumption worldwide have made it important to use energy efficiently. Energy usage from residential appliances has increased 58% since 2000, which has raised concerns about the use of energy efficient appliances. Recently in South Korea, increased fine and ultrafine dust has caused the sale of air purifiers to soar. Therefore, the government should encourage consumers to buy energy efficient air purifiers.

In this study, we have analyzed the effects of a direct incentive policy and eco-labeling in encouraging consumers to buy energy efficient air purifiers. First, we conducted a CE to quantify consumer preferences for air purifier attributes when they are making purchase decisions, following previous studies that analyzed consumer preferences for other appliances [14–17]. The RI results show that consumers' preferred attributes were price, eco-label, power consumption, coverage, CA-label, and filter grade, in that order, with the highest MWTP being for eco-labeling. Similar to previous studies, the efficiency rating, which can be inferred from power consumption and coverage, was significant in the purchase of air purifiers [22,23,33], as was the presence of an eco-label [35].

Although previous studies had considered incentive policies and energy-labeled appliances [9], studies quantifying the effects of an incentive policy on consumer purchases of energy efficient air purifiers were insufficient. Due to the problem of fine dust in Korea, the sales of air purifiers have increased, and the effect of the energy-labeling incentives on air purifiers should be analyzed before a policy is enacted. Therefore, we conducted a simulation to analyze how a direct incentive policy and eco-labeling encouraged consumers to buy energy efficient air purifiers. The simulation results show that an incentive policy that offers 10% of the price of an appliance with a first-grade energy efficiency rating, which the South Korean government tried to implement, increased the market share of first-grade efficiency rating air purifiers by 2.2%. The effects of that change in market share were an annual reduction in electricity usage of 5.9 GWh and in CO₂ emissions of 2520 t. This policy produced benefits of KRW 441,340,922 when converted into monetary units for a cost-benefits analysis. Using

eco-labeling of both first- and second-grade energy efficiency air purifiers as the incentive, the market share of the two grades together reached 80%.

Although the incentive policy was beneficial, it did not have significant effects on market share, because in the base market scenario, 60% of consumers already purchased air purifiers with first- and second-grade energy efficiency ratings. That is, consumers who value energy efficiency ratings already purchase air purifiers with high energy efficiency ratings, so the incentive policy had little effect. Another interpretation is that consumers who bought energy efficient air purifiers value attributes other than price when making their purchasing decisions. Eco-labeling brought considerable changes in market share, indicating that consumers prefer to buy environmentally friendly air purifiers whose value is certified by the government. The government should thus implement a policy that encourages enterprises to obtain eco-label certification for their energy efficient air purifiers instead of implementing an incentive policy to encourage consumers to buy energy efficient air purifiers. Although we could not quantify the eco-labeling policy, the simulation results show that both the incentive and eco-labeling policies encourage people to buy energy efficient air purifier, which confirms the findings of previous studies [9,26–28,31].

This study has some limitations despite its strengths. When conducting the consumer preference survey, we used coverage and power consumption to infer the energy efficiency rating. Thus, the data that we collected from the real market used different energy efficiency ratings from those inferred for the consumer survey. Although we revised the value with real market data, it was difficult to tell whether the effects reflected the energy efficiency rating alone or a mixture of power consumption and coverage data. In addition, our survey had 304 respondents; future studies could improve their precision by increasing the number of respondents. Finally, it was difficult to estimate the cost of implementing an eco-labeling policy, which made conducting a cost-benefit analysis of that incentive policy impossible. In other words, although eco-labeling significantly changed market share, it might be still ineffective from the perspective of a cost-benefit analysis. Future studies should work around those limitations and more precisely analyze incentive policies for energy efficient appliances.

Author Contributions: J.S. and I.-j.C. conceived and designed the research. W.K. and M.O. collected the data and analyzed it. S.K. and J.S. reviewed related previous studies. W.K., I.-j.C. and J.S. contributed to progress of research idea. All authors wrote the paper and approved the final manuscript.

Funding: This work was supported by the National Research Foundation of Korea Grant funded by the Korean Government (NRF-2017R1C1B5074293) and Korea Environment Industry & Technology Institute (KEITI) through Climate Change R&D program (funded by Korea Ministry of Environment, 2018001310001).

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Rosen, M.A. The role of energy efficiency in sustainable development. In Proceedings of the 1995 Interdisciplinary Conference: Knowledge Tools for a Sustainable Civilization. Fourth Canadian Conference on Foundations and Applications of General Science Theory, Toronto, ON, Canada, 8–10 June 1995; pp. 140–148.
2. IEA. Energy Efficiency Market Report 2018. Available online: <https://webstore.iea.org/market-report-series-energy-efficiency-2018> (accessed on 1 March 2019).
3. Air Korea. Available online: <http://www.airkorea.or.kr/> (accessed on 1 March 2019).
4. OECD Statistics. Available online: <https://stats.oecd.org> (accessed on 1 March 2019).
5. KTB Investment Stock. Available online: <https://www.ktb.co.kr/top.jsp> (accessed on 1 March 2019).
6. Banerjee, A.; Solomon, B.D. Eco-labeling for energy efficiency and sustainability: A meta-evaluation of US programs. *Energy Policy* **2003**, *31*, 109–123. [CrossRef]
7. Crosbie, T. Household energy consumption and consumer electronics: The case of television. *Energy Policy* **2008**, *36*, 2191–2199. [CrossRef]
8. Du Can, S.d.l.R.; Leventis, G.; Phadke, A.; Gopal, A. Design of incentive programs for accelerating penetration of energy-efficient appliances. *Energy Policy* **2014**, *72*, 56–66. [CrossRef]
9. Gillingham, K.; Newell, R.; Palmer, K. Energy efficiency policies: A retrospective examination. *Annu. Rev. Environ. Resour.* **2006**, *31*, 161–192. [CrossRef]

10. Lin, J. Appliance efficiency standards and labeling programs in China. *Annu. Rev. Energy Environ.* **2002**, *27*, 349–367. [[CrossRef](#)]
11. Mahlia, T.; Masjuki, H.; Choudhury, I. Development of energy labels for room air conditioner in Malaysia: Methodology and results. *Energy Convers. Manag.* **2002**, *43*, 1985–1997. [[CrossRef](#)]
12. Markandya, A.; Ortiz, R.A.; Mudgal, S.; Tinetti, B. Analysis of tax incentives for energy-efficient durables in the EU. *Energy Policy* **2009**, *37*, 5662–5674. [[CrossRef](#)]
13. Newell, R.G.; Jaffe, A.B.; Stavins, R.N. The effects of economic and policy incentives on carbon mitigation technologies. *Energy Econ.* **2006**, *28*, 563–578. [[CrossRef](#)]
14. Lee, J.; Cho, Y.; Lee, J.-D.; Lee, C.-Y. Forecasting future demand for large-screen television sets using conjoint analysis with diffusion model. *Technol. Forecast. Soc. Chang.* **2006**, *73*, 362–376. [[CrossRef](#)]
15. Waechter, S.; Sütterlin, B.; Siegrist, M. Desired and undesired effects of energy labels—An eye-tracking study. *PLoS ONE* **2015**, *10*, e0134132. [[CrossRef](#)]
16. Zhou, H.; Bukenya, J.O. Information inefficiency and willingness-to-pay for energy-efficient technology: A stated preference approach for China Energy Label. *Energy Policy* **2016**, *91*, 12–21. [[CrossRef](#)]
17. Ward, D.O.; Clark, C.D.; Jensen, K.L.; Yen, S.T.; Russell, C.S. Factors influencing willingness-to-pay for the ENERGY STAR® label. *Energy Policy* **2011**, *39*, 1450–1458. [[CrossRef](#)]
18. Anderson, S.T.; Newell, R.G. Information programs for technology adoption: The case of energy-efficiency audits. *Resour. Energy Econ.* **2004**, *26*, 27–50. [[CrossRef](#)]
19. Mills, B.; Schleich, J. What’s driving energy efficient appliance label awareness and purchase propensity? *Energy Policy* **2010**, *38*, 814–825. [[CrossRef](#)]
20. Bertoldi, P.; Atanasiu, B. *Electricity Consumption and Efficiency Trends in the Enlarged European Union*; IES–JRC, European Union: Brussels, Belgium, 2007.
21. IEA. Policy Pathway—Monitoring, Verification and Enforcement. 2017. Available online: <https://www.iea.org/topics/energyefficiency/appliancesandequipment> (accessed on 1 March 2019).
22. Costa, D.L.; Kahn, M.E. Energy conservation “nudges” and environmentalist ideology: Evidence from a randomized residential electricity field experiment. *J. Eur. Econ. Assoc.* **2013**, *11*, 680–702. [[CrossRef](#)]
23. Dolan, P.; Metcalfe, R. *Neighbors, Knowledge, and Nuggets: Two Natural Field Experiments on the Role of Incentives on Energy Conservation*; Becker Friedman Institute for Research in Economics: Chicago, IL, USA, 2015.
24. Mahlia, T.; Masjuki, H.; Choudhury, I.; Ghazali, N. Economical and environmental impact of room air conditioners energy labels in Malaysia. *Energy Convers. Manag.* **2002**, *43*, 2509–2520. [[CrossRef](#)]
25. Yilmaz, S.; Majcen, D.; Heidari, M.; Mahmoodi, J.; Brosch, T.; Patel, M.K. Analysis of the impact of energy efficiency labelling and potential changes on electricity demand reduction of white goods using a stock model: The case of Switzerland. *Appl. Energy* **2019**, *239*, 117–132. [[CrossRef](#)]
26. Dieu-Hang, T.; Grafton, R.Q.; Martínez-Españeira, R.; Garcia-Valiñas, M. Household adoption of energy and water-efficient appliances: An analysis of attitudes, labelling and complementary green behaviours in selected OECD countries. *J. Environ. Manag.* **2017**, *197*, 140–150. [[CrossRef](#)]
27. Wang, Z.; Wang, X.; Guo, D. Policy implications of the purchasing intentions towards energy-efficient appliances among China’s urban residents: Do subsidies work? *Energy Policy* **2017**, *102*, 430–439. [[CrossRef](#)]
28. Zhao, C.; Zhang, M.; Wang, W. Exploring the influence of severe haze pollution on residents’ intention to purchase energy-saving appliances. *J. Clean. Prod.* **2019**, *212*, 1536–1543. [[CrossRef](#)]
29. Shen, J.; Saijo, T. Does an energy efficiency label alter consumers’ purchasing decisions? A latent class approach based on a stated choice experiment in Shanghai. *J. Environ. Manag.* **2009**, *90*, 3561–3573. [[CrossRef](#)] [[PubMed](#)]
30. Stadelmann, M.; Schubert, R. How do different designs of energy labels influence purchases of household appliances? a field study in Switzerland. *Ecol. Econ.* **2018**, *144*, 112–123. [[CrossRef](#)]
31. Datta, S.; Gulati, S. Utility rebates for ENERGY STAR appliances: Are they effective? *J. Environ. Econ. Manag.* **2014**, *68*, 480–506. [[CrossRef](#)]
32. Gillingham, K.; Palmer, K. Bridging the energy efficiency gap: Policy insights from economic theory and empirical evidence. *Rev. Environ. Econ. Policy* **2014**, *8*, 18–38. [[CrossRef](#)]
33. Kelly, G. Sustainability at home: Policy measures for energy-efficient appliances. *Renew. Sustain. Energy Rev.* **2012**, *16*, 6851–6860. [[CrossRef](#)]
34. Zeng, L.; Yu, Y.; Li, J. China’s promoting energy-efficient products for the benefit of the people program in 2012: Results and analysis of the consumer impact study. *Appl. Energy* **2014**, *133*, 22–32. [[CrossRef](#)]

35. Goh, S.K.; Balaji, M. Linking green skepticism to green purchase behavior. *J. Clean. Prod.* **2016**, *131*, 629–638. [[CrossRef](#)]
36. Dahl, R. Green washing: Do you know what you're buying? *Environ. Health Perspect.* **2010**, *118*, A246–A252. [[CrossRef](#)]
37. Chen, Y.-S.; Lin, C.-L.; Chang, C.-H. The influence of greenwash on green word-of-mouth (green WOM): The mediation effects of green perceived quality and green satisfaction. *Qual. Quant.* **2014**, *48*, 2411–2425. [[CrossRef](#)]
38. Lyon, T.P.; Maxwell, J.W. Greenwash: Corporate environmental disclosure under threat of audit. *J. Econ. Manag. Strategy* **2011**, *20*, 3–41. [[CrossRef](#)]
39. Zhang, L.; Li, D.; Cao, C.; Huang, S. The influence of greenwashing perception on green purchasing intentions: The mediating role of green word-of-mouth and moderating role of green concern. *J. Clean. Prod.* **2018**, *187*, 740–750. [[CrossRef](#)]
40. Laufer, W.S. Social accountability and corporate greenwashing. *Journal of business ethics* **2003**, *43*, 253–261. [[CrossRef](#)]
41. Polonsky, M.J.; Grau, S.L.; Garma, R. The New Greenwash?: Potential Marketing Problems with Carbon Offsets. *Int. J. Bus. Stud.* **2010**, *18*, 49.
42. Hess, S.; Stathopoulos, A.; Daly, A. Allowing for heterogeneous decision rules in discrete choice models: An approach and four case studies. *Transportation* **2012**, *39*, 565–591. [[CrossRef](#)]
43. McFadden, D. *Conditional Logit Analysis of Qualitative Choice Behavior*; Wiley: New York, NY, USA, 1973.
44. Train, K.E. *Discrete Choice Methods with Simulation*; Cambridge University Press: Cambridge, UK, 2009.
45. Can, A. Specification and estimation of hedonic housing price models. *Reg. Sci. Urban Econ.* **1992**, *22*, 453–474. [[CrossRef](#)]
46. Vanslebrouck, I.; Van Huylenbroeck, G.; Van Meensel, J. Impact of agriculture on rural tourism: A hedonic pricing approach. *J. Agric. Econ.* **2005**, *56*, 17–30. [[CrossRef](#)]
47. Greening, L.A.; Sanstad, A.H.; McMahon, J.E. Effects of appliance standards on product price and attributes: An hedonic pricing model. *J. Regul. Econ.* **1997**, *11*, 181–194. [[CrossRef](#)]
48. Louviere, J.J. Conjoint analysis modelling of stated preferences. *J. Transp. Econ. Policy* **1988**, *22*, 93–119.
49. Verma, R.; Iqbal, Z.; Plaschka, G. Understanding customer choices in e-financial services. *Calif. Manag. Rev.* **2004**, *46*, 43–67. [[CrossRef](#)]
50. Green, P.E.; Srinivasan, V. Conjoint analysis in consumer research: Issues and outlook. *J. Consum. Res.* **1978**, *5*, 103–123. [[CrossRef](#)]
51. Jain, M.; Rao, A.B.; Patwardhan, A. Consumer preference for labels in the purchase decisions of air conditioners in India. *Energy Sustain. Dev.* **2018**, *42*, 24–31. [[CrossRef](#)]
52. Jeong, G.; Kim, Y. The effects of energy efficiency and environmental labels on appliance choice in South Korea. *Energy Effic.* **2015**, *8*, 559–576. [[CrossRef](#)]
53. Shin, J.; Park, Y.; Lee, D. Google TV or Apple TV?—The Reasons for Smart TV Failure and a User-Centered Strategy for the Success of Smart TV. *Sustainability* **2015**, *7*, 15955–15966. [[CrossRef](#)]
54. Sim Ong, F.; Kitchen, P.J.; Shiuan Chew, S. Marketing a consumer durable brand in Malaysia: A conjoint analysis and market simulation. *J. Consum. Mark.* **2010**, *27*, 507–515. [[CrossRef](#)]
55. Ito, K.; Zhang, S. *Willingness to Pay for Clean Air: Evidence from Air Purifier Markets in China*; National Bureau of Economic Research: Cambridge, MA, USA, 2016.
56. Korea Ministry of Trade, Industry and Energy. *Regulations for Operation of Efficiency Management Equipment and Materials*; Korea Ministry of Trade, Industry and Energy: Sejong-si, Korea, 2017. (In Korean)
57. Sammer, K.; Wüstenhagen, R. The influence of eco-labelling on consumer behaviour—Results of a discrete choice analysis for washing machines. *Bus. Strategy Environ.* **2006**, *15*, 185–199. [[CrossRef](#)]
58. Korea Ministry of Environment. *Basic Law of Law Carbon and Green Growth*; Korea Ministry of Environment: Sejong-si, Korea, 2018. (In Korean)
59. KOSIS. Available online: <http://kosis.kr/> (accessed on 1 March 2019).

60. KOREA POWER EXCHANGE. Available online: <https://www.kpx.or.kr/> (accessed on 10 March 2019).
61. KRX. Available online: <http://www.krx.co.kr/> (accessed on 1 March 2019).



© 2019 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<http://creativecommons.org/licenses/by/4.0/>).