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Abstract

We investigate whether the contrasting set of transportation policies in Korea—reductions in fuel taxes and increases in diesel automobile prices—has decreased emissions. Using a random-coefficient discrete choice model and hypothetical policy sets, we estimate the automobile demand of consumers, the market share of cars by fuel type, and total emissions, assuming that consumer preferences for driving costs change over time. Then, we separately analyze the effect of each policy set on automobile sales and emissions, particularly carbon dioxide, nitrogen oxide, and particulate matter. Our analyses reveal that Korean consumers have become more sensitive toward fuel costs over time and that the emission consequences of Korean policies depend on consumer preferences.

Keywords: Discrete Choice, Demand Estimation, Emissions, Transportation, Fuel Cost

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1 Introduction

To mitigate the threat of increasing emissions from the transportation sector, many countries have tried to reduce emissions using various market-based policy instruments. There are three main policy options to reduce emissions in the transportation sector: financial incentives, fuel tax regulations, and subsidies. Financial incentives are offered to reduce automobile tax or automobile prices and thus promote consumers' purchases of cars. Fuel tax regulations refer to the changes in fuel tax rates designed to incentivize drivers to drive less. Subsidies are the provision of monetary incentives to reduce automobile prices for eligible alternative fuel source cars such as hybrids, plug-in hybrids, and electric vehicles (EVs).

Financial incentives in Korea take two forms: changing fuel tax rates on gasoline, diesel, and liquefied petroleum gas (LPG), and subsidizing the purchases of environmentally friendly automobiles to increase their sales. However, Korea, the world's seventh largest CO_2 emitter in 2019 according to the International Energy Agency, has created a contrasting set of policies to tackle emissions, which steadily increased from 2008 to 2017. For example, from September 2017 to December 2018, it abolished all financial incentives and subsidies for diesel-fueled vehicles while simultaneously decreasing diesel and gasoline tax rates. By abolishing the so-called Clean Diesel policy, the Korean government hoped to make consumers aware of the environmental harm of diesel. Through fuel tax reductions, the Korean government aimed to reduce consumers' financial burden. As a result, diesel automobile sales in Korea initially decreased with the government's announcement of the removal of financial incentives, but began to increase again after the fuel tax adjustments. This problem demands a quantitative investigation on which policy sets have the most potential to reduce emissions.

To this end, we first create a "driving cost" variable, or fuel cost in Korean Won (henceforth KRW) per driving unit in kilometers. Then, we take into account that consumer preferences for driving cost change over time. Although conventional models used in the literature typically assume that consumer preferences do not change over time, we allow time-varying consumer preferences for distance costs to separately determine the effects of consumer preferences induced by the policy changes on automobile choice.

We collect and use monthly aggregate-level data on the Korean automobile industry. With these data, we first estimate the demand, allowing consumer preferences regarding driving costs to evolve over time and with heterogeneous automobile prices and driving costs. Our estimation results confirm that consumer preferences regarding driving costs have changed over time; they exhibit a decreasing trend, implying that Korean consumers are becoming more fuel cost-sensitive. For example, consumers in the first quarter of 2017 (2017Q1) are less sensitive towards the driving costs compared to the consumers in the fourth quarter of 2018 (2018Q4). Our estimation results also support heterogeneity exists in consumers' evaluation of automobile prices and driving costs.

Our main contribution is that we decompose the effects of changes in consumer preferences and policies on emissions from counterfactual simulations. Using the estimated parameters, we conduct counterfactual simulations by letting consumers in 2017Q1 purchase from the set of automobile brands that were available in 2018Q4, and vice versa. Our counterfactual simulations consist of a 10% increase in the diesel fuel tax and a 10% increase in the prices of diesel automobiles. We then estimate the impacts of them on automobile demand and emissions.

This study contributes to two strands of literature. First, this study investigates the direct impact of consumer preferences on emissions by simulating the impact of consumer preferences and policies. Previous literature, which either indirectly measures consumer preferences by endogenizing technological improvements (Klier and Linn 2012, Knittel 2012) or explores the impacts of financial incentives on automobile demand (Potoglou and S.Kanaroglou 2007, Ziegler 2012, and Al-Alawi and Bradley 2013 have found that consumer demand for hybrid cars increases with greater financial incentives). Other studies have investigated the combined impact of technological advancement and consumer behavior on emissions: DHaultfoeuille et al. 2016 considered consumers' environmental awareness as an essential factor and investigated the impacts of technological development on emissions. However, heretofore, there has been no research that investigates the combined impact of policy changes and the evolution of consumer preference, at least to the authors' knowledge. Therefore, this study contributes to the existing literature by means of an analysis that decouples changes in consumer preference and policy.

Second, this study also contributes to the research on energy policy evaluation. Previous research (Choo and Mokhtarian 2004, Sprei and Bauner 2011, Hackbarth and Madlener 2013, and Kim, Rasouli and Timmermans 2014) has found that fuel economy levels, which are improved through the implementation of fuel economy standards and financial incentives, are an important factor affecting consumers' automobile purchases. However, although automobile demand has been increasing, the effectiveness of these incentives and policies in reducing emissions has not yet been evaluated. Intuitively, the increased demand for automobiles may increase emissions so this is an important quantitative exercise to perform. For example, Gallagher and Muehlegger 2011, Diamond 2009, Sallee 2011, and Jenn, Azevedo and Ferreira 2013 have argued that the total number of automobiles might increase if they are not bought by environmentally cautious consumers. This would ultimately increase emissions, as stated in Bitsche and Gutmann 2004, Haan, Mueller and Peters 2006, DeHaan, G.Mueller and Scholz 2009, Greening, Greene and Difiglio 2000, West, Hoekstra, Meer and Puller 2017, and Yoo, Koh, Yoshida and Wakamori 2019. Our research separately conducts counterfactual simulations and calculates and decomposes the effects of these factors on emissions.

2 Background

2.1 Policy Background

In the late 2000s, the Korean government tried to reduce emissions from the transportation sector by promoting the purchase and use of diesel cars. For example, in 2009, it announced the provision of tax incentives to designated Clean Diesel cars that satisfied Euro 5 Standards, with the implementation of the policy by 2010. Under the Clean Diesel policy, diesel car owners were also exempt from parking fees and congestion charges.

By the early 2010s, sales of diesel vehicles in Korea had increased significantly; the ratio of diesel automobile sales to total automobile sales rose from 36.3% in 2011 to 39.4% in 2014. Meanwhile, the stock of diesel cars reached 9.58 million of the 22.53 million cars nationwide in 2017. Under this policy, foreign car manufacturers such as Volkswagen and BMW included 2,000 cc diesel engines in their Korean market products. In turn, the penetration rate of diesel cars in Korea increased significantly.

However, this changed with the "Dieselgate" scandal in 2015, when the US Environmental Protection Agency found that the Volkswagen Group had manipulated the emissions test results for diesel automobiles by installing illegal software into their products. As a result, many Europeans started to criticize the use of all internal combustion engines. Indeed, France and Britain plan to ban the sale of new cars that only have internal combustion engines by 2040. Dieselgate also resulted in Korean consumers losing trust in diesel automobiles.

In light of Korean citizens' distrust of diesel automobiles, the Korean government abolished the Clean Diesel policy and introduced a bill to ban sales of diesel-powered cars to curb particulate matter (PM) emissions. The election of President Moon Jae-In in April 2017 led to expectations by the public and media of diesel subsidy reductions[1] as early as May 2017. The plan, enacted on November 8, 2018, called for the removal of the criteria for

[1]Source: https://biz.chosun.com/site/data/html_dir/2017/05/10/2017051000418.html

"low-pollution diesel cars" and financial incentives, such as reduced parking fees and congestion charges, for 950,000 diesel cars that had been previously deemed as low-polluting. In particular, the government set a goal of eliminating the public sector's diesel car stock by 2030.

However, there was another concurrent and contrasting change in Korean energy policy. Citing soaring fuel costs and the need to stimulate the economy and secure jobs, the Korean government announced lower fuel taxes on November 6, 2018, cutting oil taxes on gasoline, diesel, and LPG by 10%. The average gasoline price at gas stations nationwide in the second week of October 2018 was KRW 1,674.9/liter, up by KRW 15.4 from the previous week. The price of diesel for automobiles also rose by KRW 16.5 to KRW 1,477.9/liter (Korea National Oil Corporation), whereas crude oil, which South Korea mostly imports, stood at USD 82 per barrel. The Deputy Prime Minister of Korea argued that since oil prices had exceeded USD 80 per barrel, this could place pressure on small business owners and working-class people and that a cut in oil taxes would help the economy by addressing their difficulties and increasing their disposable income.

Thus, gasoline taxes fell from KRW 745.89/liter to KRW 643.50/liter, diesel taxes from KRW 528.75 to KRW 449.79/liter, and LPG taxes from KRW 528.75 to KRW 449.79/liter (www.opinet.co.kr). This was the first reduction in fuel taxes in 10 years, with the previous cuts occurring when international oil prices were as high as USD 140 per barrel. Other related fuel and automobile taxes decreased as well, bringing the overall reduction in taxes to approximately 15%. These tax cuts were a six-month temporary measure in response to the spike in crude oil prices and aimed to alleviate the economic effects of high oil prices on Korean households and businesses.

The Clean Diesel policy was abolished to improve the Korean automobile market's response to the environmentally damaging prospects of diesel fuel and ultimately reduce carbon dioxide(CO_2), nitrogen oxide (NOx), and particulate matter (PM) emissions. Therefore, as regards to updating environmental policies, the decrease in fuel taxes and resulting increase in demand for fuel seem to be contrasting elements.

2.2 Industry Background

The policy objective of the Korean government is unclear. Although the government announced that the gradual reduction in diesel vehicles was its ultimate objective, if diesel and other fuel costs decrease, consumers will be induced to purchase more automobiles. Because the increased financial incentives enable consumers to replace their cars or buy new ones, these incentives can eventually increase car sales and counteract the abolition of the Clean Diesel policy, ultimately increasing emissions.

Figure 1 supports our research motivation by showing that automobile demand and fuel costs move together. Panel (A) shows the costs of diesel and gasoline, Panel (B) displays gasoline and diesel car prices, and Panel (C) displays the trend of gasoline and diesel cars sales. In all three panels, we divide the policy period into three phases: Phase 1 includes the period from January 2017 to September 2017, where no policy changes occurred. Phase 2 is from September 2017 to October 2018, when diesel car prices increased. Finally, Phase 3 starts in October 2018 to January 2019, when the government decreased diesel prices (we henceforth refer to diesel fuel prices and diesel car prices separately, with "diesel prices" indicating the former). As shown in Panel (A), diesel prices fluctuated more than those of gasoline, increased rapidly at the start of Phase 2, and decreased rapidly at the end of Phase 2.[2] The diesel price decreased again in Phase 3. Although diesel prices show significant fluctuations, the raw price of diesel was always lower than that of gasoline or LPG.

Panel (B) of Figure 1 displays the time trends of gasoline car (and hybrid electric vehicle (HEV)) prices and diesel car prices. Consistent with these policies, we observe an increase

[2] This rapid fall in diesel prices is mainly due to the International Diesel Price Shock [OilPrice.com (2018.6.29), "Global Energy Advisory 29th June 2018"].

in diesel car prices in Phase 2.[3]

Panel (C) of Figure 1 shows the number of diesel cars sold according to the policy changes. We observe two things; we first observe the fall in diesel car sales from March 2017 to September 2017, even before the beginning of Phase 2. As noted before, we attribute the fall of diesel car sales to the general public's expectations of the removal of diesel car subsidies as early as May 2017. In fact, this was part of an election platform of the Moon administration, which was newly elected into office in April 2017. Therefore, consumers were likely to be aware of this policy before the beginning of Phase 2.

In addition, sales of diesel cars decreased significantly around in the beginning of Phase 2 and increased again in Phase 3. Gasoline car sales showed similar trends. We attribute the similar time trends of diesel and gasoline automobile sales to seasonal demand fluctuations, including seasonal sales promotions in the Korean automobile industry. More importantly, at the beginning of Phase 2, even with such seasonality, the difference between diesel automobile sales and gasoline and HEV automobile sales decreased as diesel car sales decreased during Phase 2 (mostly in 2018) compared with the same period in 2017. This may have been related to the increase in diesel car prices, as shown in Panel (B).

The time series data suggest that changes in Korean energy policy may have affected demand for diesel cars. Thus, in this study, we examine demand for such automobiles. Although fuel prices actually started to fall in October 2018, the policy was announced in 2018Q2. Thus, we expect that consumers made their purchase decisions before the actual policy change.

Further, fuel costs decreased and the number of new cars bought increased significantly in Phase 3 compared with in Phase 2. These trends are likely to increase aggregate emissions,

[3] We attribute the fall in gasoline car prices by 0.75–1.15 million KRW around November 2017 to January 2018 to a widely advertised year-end automobile sale. We also attribute the fall in gasoline automobile prices in June 2018 to the release of the new SM3 model by Renault Samsung Motors, which was around 1 million KRW less expensive than the average automobile at the time.

as travel distances did not decrease from 2017 to 2018.[4] Hence, Korean policies may induce more emissions, which is why they need to be investigated to assess their impact on consumer preferences, automobile demand, and emissions.

[4] According to the Korean Transportation Statistics (2019) published by the Ministry of Land, Infrastructure and Transport, travel distance in Korea has increased steadily from 2014, with a rise of 2.3% in 2018 compared with 2017.

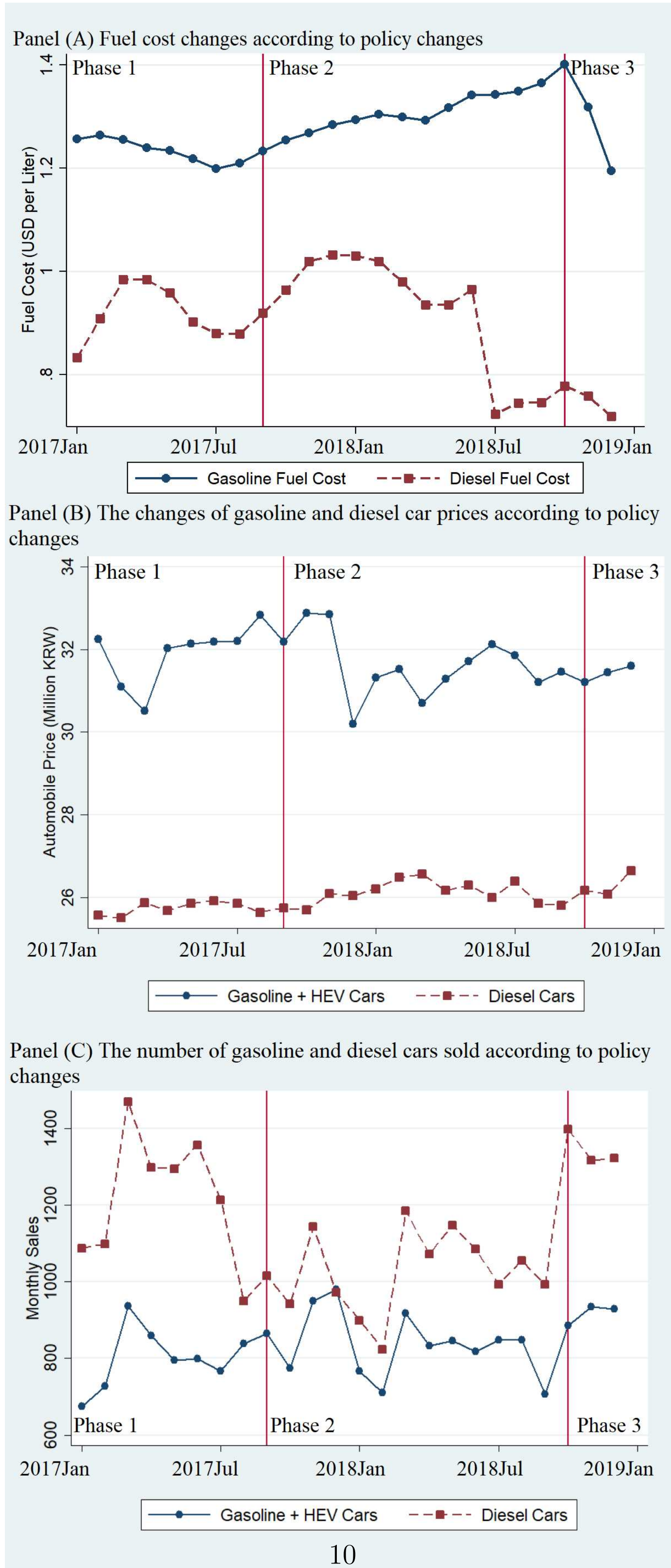

Figure 1: Timely Changes in Fuel Costs According to Policy Changes

3 Empirical Methods

3.1 Data

We first collect monthly data on new car sales, vehicle attributes, and fuel costs. The data are obtained from a Korean website, auto.danawa.com, which provides information on vehicle attributes such as horsepower, displacement, weight, fuel type, and fuel economy for all Korean domestic manufacturers (Hyundai, Kia, GM, Samsung, and SsangYong). In total, we collect data on 3,320 vehicle models sold between January 2017 and December 2018. By "model," we also refer to all specifications within the same model; for instance, our data include at least 20 specifications for the Hyundai Sonata, a flagship product of the Hyundai Motor Company. These specifications differ in fuel type and vehicle attributes (i.e., displacement, fuel economy, weight, size, and riding capacity). Considering all these different specifications leads to 3,320 vehicle models or specifications in our data (we use the terms "vehicle models" and "specifications" interchangeably henceforth).

One distinctive characteristic of the Korean automobile market is that the Korea Energy Agency website provides information on the CO_2 emissions per kilometer of each specification. This statistic is the product of the emissions factor and fuel source. Table 1 displays the descriptive statistics of the variables. Approximately 130 car models are available for each month in our sample period. In Table 1, the data indicate the differences in the vehicle attributes by automobile type. First, gasoline and diesel cars account for more than 80% of the market share. Second, surprisingly, although hybrid cars have higher average fuel economy (17.484 km/l), the data show that gasoline cars have the highest maximum fuel efficiency level. This is because hybrid vehicles are generally heavier than gasoline cars. As hybrid vehicles are more expensive than gasoline cars on average, we anticipate that consumers who want to purchase a fuel-efficient vehicle would choose gasoline cars rather than HEVs. We also found no significant differences in the other vehicle attributes such as weight and length.

There are three car types in Korea, namely, minivans, small cars, and regular cars. To control for car type, we include a dummy variable for minivans, which are cars with a displacement of less than 1,000 cc, a length less than 3,600 mm, a width less than 1,600 mm, and a height less than 2,000 mm. We also add a small cars dummy variable, which refers to a vehicle slightly larger than minivans but smaller than regular vehicles; that is, a car with a displacement less than 1,600 cc but higher than 1,000 cc, a length less than 4,6700 mm, a width less than 1,700 mm, and a height less than 2,000 mm.[5]

Although the table shows the raw data for each variable, when estimating the model, we take the logarithm of all the variables to better interpret the results in terms of changes in those variables.

[5] We do not designate a separate dummy variable for regular cars, our base car category.

Table 1: Descriptive Statistics

	N	Mean	Std. Dev.	Min.	Max.
Gasoline Cars					
Market Share	1,692	49.52%			
Automobile Price (in KRW Million)	1,692	31.70	20.20	9.45	119.0
Units sold	1,692	877	2182.735	1	73,674
Fuel Efficiency (km/l)	1,692	11.712	2.665	7.3	22.4
Weight (kg)	1,692	1,504.352	319.018	890	2,225
Length (mm)	1,692	4,659.324	430.790	3,595	5,205
Riding Capacity	1,692	4.75	0.88	2	8
Fuel Cost (KRW)	1,692	1,536.524	64.7120	1,433.13	1,681.12
Diesel Cars					
Market Share	1,008	37.81%			
Automobile Price (in KRW Million)	1,008	26.00	6.455	8.38	119.0
Units sold	1,008	1,123.651	1,772.983	1	10,064
Fuel Efficiency (km/l)	1,008	13.931	2.680	8	19.1
Weight (kg)	1,008	1,651.964	266.424	1,180	2,320
Length (mm)	1,008	4,674.653	289.911	4,060	5,150
Riding Capacity	1,008	5.09	0.88	3	9
Fuel Cost (KRW)	1,008	1338.6	65.906	1,229.81	1,485.02
LPG Cars					
Market Share	314	7.69%			
Automobile Price (in KRW Million)	314	18.50	6.798	8.380	31.90
Units sold	314	733.176	945.513	1	5,241
Fuel Efficiency (km/l)	314	8.821	1.014	6.5	10.6
Weight (kg)	314	1,322.118	306.334	735	1,690
Length (mm)	314	4,430.446	666.325	3,235	5,115
Riding Capacity	314	4.61	1.27	2	7
Fuel Cost (KRW)	314	1082.449	120.744	863.35	1238.37
HEVs					
Market Share	179	3.67%			
Automobile Price (in KRW Million)	179	32.30	4.609	23.50	39.40
Units sold	179	614.832	772.439	1	3,040
Fuel Efficiency (km/l)	179	17.484	1.354	11.3	19.5
Weight (kg)	179	1,605.084	84.452	1,425	1,725
Length (mm)	179	4,751.536	231.684	4,355	4,970
Riding Capacity	179	5	0	5	5
Fuel Cost (KRW)	179	1,536.524	64.7120	1,433.13	1,681.12
EVs					
Market Share	109	1.30%			
Automobile Price (in KRW Million)	109	38.00	10.00	15.00	47.80
Units sold	109	357.560	491.664	1	2,906
Fuel Efficiency (kw/h)	109	10.003	7.296	4.4	22.4
Weight (kg)	109	1,360.945	415.072	175	1,755
Length (mm)	109	4,046.266	781.361	2,338	4,750
Riding Capacity	109	4.26	1.30	2	5
Fuel Cost (KRW)	109	86.9	0	86.9	86.9

3.2 Demand Estimations

To estimate automobile demand, we employ the random-coefficient discrete choice model developed by Berry et al., 1995. We assume that consumers have heterogeneous preferences for automobile prices and driving costs and that their preferences for driving costs change over time. We calculate the driving cost per kilometer (KRW/km), simply "driving cost" hereafter, as

$$DC_{j,a,t} = FC_{a,t} * (1/E_{j,t}), \tag{1}$$

where $DC_{j,a,t}$ is the driving cost of automobile j of fuel type a at time (quarter) t, $FC_{a,t}$ is the fuel cost of car type a at time t, and $E_{j,t}$ is the fuel economy of automobile j at time t. The inverse value of fuel economy $(1/E_{j,t})$ represents fuel usage per unit driving distance (1 km), which has also been used by Yoo, Koh, Yoshida and Wakamori 2019.[6] From the following model descriptions, we drop the subscript a for notational simplicity.

Given that our data consist of aggregated market shares and micro-level product characteristics, we use the discrete-choice demand model developed by Berry 1994 and Berry, Levinsohn and Pakes 1995. Let us assume that consumer i, $i = 1, \ldots, M$, buys car j from the available set of automobiles in year t, denoted by $\mathcal{J}_t$. Consumer i always has the option not to purchase any automobile, which is expressed as $j = 0$ and is called the "outside option." In other words, for any t, $j = 0$ is included in $\mathcal{J}_t$. The indirect utility of consumer i choosing automobile j in year t is given by

$$u_{ijt} = \boldsymbol{x}'_{jt}\boldsymbol{\beta}_{it} - \alpha_i p_{jt} + \xi_j + \epsilon_{ijt}, \tag{2}$$

where $\boldsymbol{x}_{jt}$ denotes the vector of observed vehicle attributes such as the displacement and weight of automobile j in year t. We also treat driving cost DC_{jt} as a vehicle attribute, as it reflects fuel economy. However, unlike other vehicle attributes, the increase in driving cost

[6] As our model contains EVs, we calculate EVs' distance costs as charge cost * fuel economy.

leads to an increase in the monetary burden of consumers, therefore decreasing their utility.

p_{jt} denotes the *after* tax/subsidy price of automobile j in year t. ξ_j denotes an unobserved attribute of automobile j from an econometric perspective, which is only observed by consumers and car manufacturers and may be correlated with automobile prices. ϵ_{ijt} denotes a random utility shock. α_i is a heterogeneous coefficient that depends on consumer i, whereas $\boldsymbol{\beta}_{it}$, a vector of consumers' evaluations of each automobile attribute, is assumed to be heterogeneous across consumers as well as time-varying to capture changes in consumer preferences.

In this study, we treat automobile price p_{jt} and driving cost as heterogeneous variables. Therefore, $(\alpha_i, \boldsymbol{\beta_{it}})$ is a vector of the random coefficients to be estimated and is assumed to vary by individual. Specifically, to capture the heterogeneity in consumer preferences and their potential evolution, we assume the following functional form for β_{itk} and α_i, where the subscript k represents the k-th element of an automobile's characteristics:

$$\begin{aligned} \beta_{itk} &= \beta^m_{tk} + \beta^v_{tk}\sigma_{itk}, \\ \alpha_i &= \alpha^m + \alpha^v \sigma_i, \end{aligned} \tag{3}$$

where σ represents individual heterogeneity, which follows the standard normal distribution, namely, $\sigma_{itk} \sim N(0,1)$ and $\sigma_i \sim N(0,1)$.[7] β^m_{tk} and α^m denote their respective mean coefficients, while β^v_{tk} and α^v respectively show the standard deviations of consumer preferences for the k-th element of the automobile's characteristics (prices), capturing the average preferences and heterogeneity of consumers. For example, consider the situation in which some consumers positively evaluate powerful automobiles with a high level of horsepower, whereas others do not. In such a case, β^m_{tk} captures consumers' mean preference for horsepower, whereas β^v_{tk} captures the heterogeneity in consumer preferences for horsepower.

[7] We drop the subscript k for automobile price is a scalar, unlike the vector for multiple vehicle characteristics in the equation above.

We use a time-varying (quarterly) coefficient for driving cost preference. The coefficient for the driving cost of consumer i for automobile j at time t, which is an element of the vector of the vehicle attribute characteristics $\boldsymbol{x_{jt}}$ (we assume $k = 1$ to indicate the driving cost characteristic), can be expressed as

$$\begin{aligned} \beta_{it1} = \beta^m_{Base,DC} + \beta^v_{Base,DC}\sigma_{i1} \\ +\beta^m_{2017Q2,DC} + \beta^m_{2017Q3,DC} + \beta^m_{2017Q4,DC} \\ +\beta^m_{2018Q1,DC} + \beta^m_{2018Q2,DC} + \beta^m_{2018Q3,DC} + \beta^m_{2018Q4,DC} \\ \text{where} \quad \sigma_{i1} \sim N(0,1), \end{aligned} \tag{4}$$

where $\beta^m_{Base,DC}$ is the mean driving cost preference in the base quarter (2017Q1) and $\beta^v_{Base,DC}\sigma_{i1}$ is the random coefficient component of DC_{jt} in the base quarter. $\beta^m_{2017Q2,DC}$ stands for the mean of consumer preferences for driving cost in 2017Q2, $\beta^m_{2017Q3,DC}$ is the mean in 2017Q3, and so on. One way to interpret Equation (4) is that it measures the base preference for driving cost and its heterogeneity, whereas it has time-varying mean coefficients for every quarter.

In addition, we assume driving cost to be heterogeneous as well as the automobile price because we suppose that it is closer to fuel costs than fuel economy, which is a vehicle attribute. We find relatively more variance in fuel costs, which change by month, compared with fuel economy, which is unchanged until the model exits the market (which usually takes 5–10 years). Thus, consumers have more heterogeneous preferences for fuel costs than for fuel economy. Furthermore, as automobile demand also depends on fuel costs and fuel cost-related policies, as shown in Panel (B) in Figure 1, we set our model to include driving cost variations. Substituting Equation (3) into Equation (2) and rearranging the terms (i.e., gathering the variables unrelated to individual i into one group and those related to i into another), we have

$$
\begin{aligned}
u_{ijt} &= \sum_k x_{jkt}(\beta^m_{tk} + \beta^v_{tk}\sigma_{itk}) - \alpha_i p_{jt} + \xi_j + \epsilon_{ijt}, \qquad (5)\\
&= \underbrace{\sum_k x_{jkt}\beta^m_{tk} - \alpha^m p_{jt} + \xi_j}_{\equiv \delta_{jt}} + \underbrace{\sum_k x_{jkt}\beta^v_{tk}\sigma_{itk} + \alpha^v p_{jt}\sigma_i}_{\equiv \mu_{ijt}} + \epsilon_{ijt},
\end{aligned}
$$

where we define the first term on the right-hand side as mean utility, which does not depend on any individual i but depends only on product j, and the second term as the deviation from the mean, which depends on both individual i and product j.

For notational simplicity, we suppress the subscript t in the model description below. We assume that consumer i maximizes his/her utility by choosing product j that provides the highest utility. In other words, he/she chooses product j if and only if $u_{ij} \geq u_{il}$ for any $l \in \mathcal{J}\backslash\{j\}$. Each individual is now characterized by $(\boldsymbol{\beta}_i, \boldsymbol{\epsilon}_i)$, where $\boldsymbol{\epsilon}_i = [\epsilon_{i0}, \ldots, \epsilon_{iJ}]$. Integrating all consumers' automobile choices, we obtain the market share of product j as

$$
\begin{aligned}
& s_j(\theta|\boldsymbol{p}, \boldsymbol{x}, \boldsymbol{\xi}) = \int_{A_j \in M} dF(\epsilon) \qquad (6)\\
& \text{with } \; A_j = \{(\boldsymbol{\beta}_i, \boldsymbol{\epsilon}_i) | u_{ij}(\theta|\boldsymbol{x}, p, \xi) \geq u_{il}(\theta|\boldsymbol{x}, p, \xi)\},
\end{aligned}
$$

where θ is the set of parameters $(\alpha, \boldsymbol{\beta}^m, \boldsymbol{\beta}^v)$ and A_j is the set of individuals who purchase automobile j. As is common in the literature, we assume that ϵ_{ij} follows the extreme value Type I distribution, $F(\epsilon)$, which enables us to obtain an analytical formula for the choice probability that individual i chooses product j:

$$
\Pr(d_{ijt}|\boldsymbol{\theta}) = \frac{\exp(\delta_{jt} + \mu_{ijt})}{1 + \sum_{l \in J_t} \exp(\delta_{lt} + \mu_{ilt})}, \qquad (7)
$$

where d_{ijt} is an indicator function that takes a value of one when consumer i purchases automobile j in year t and zero otherwise.

Then, we aggregate consumers' purchase decisions to obtain the market shares for product j and the outside option:

$$\begin{aligned} s_{jt}(\theta|\boldsymbol{p},\boldsymbol{x},\boldsymbol{\xi}) &= \frac{\exp(\delta_{jt})}{1+\sum_{l\in J_t}\exp(\delta_{lt})}, \\ s_{0t}(\theta|\boldsymbol{p},\boldsymbol{x},\boldsymbol{\xi}) &= \frac{\exp(0)}{1+\sum_{l\in J_t}\exp(\delta_{lt})}. \end{aligned}$$

Next, we take the log-difference of the two equations, akin to the inversion technique developed by Berry 1994, to yield the following regression model:

$$\ln(s_{jt}) - \ln(s_{0t}) = \delta_{jt} = \boldsymbol{x}'_{jt}\boldsymbol{\beta}_t - \alpha p_{jt} + \xi_{jt}. \tag{8}$$

Therefore, viewing ξ_{jt} as error terms, we can estimate this model using ordinary least squares (OLS). However, we suspect a correlation between p_{jt} and ξ_{jt} because if consumers appreciate unobserved product characteristics, ξ_{jt}, then the firm must charge higher prices. Thus, we use an instrumental variable (IV) approach to solve this issue, as explained in Section 3.3.

After deriving a utility function from the 2017Q1–2018Q4 sales data, we model consumer preferences for the purchase of a new car to show the policy effects that explain how vehicle characteristics affect consumers' vehicle choices and whether consumer preferences differ based on automobile prices.

3.3 Estimation

The price of automobile j may be correlated with an unobserved product attribute, ξ_j, as previously mentioned. This is because firms that produce automobile j can increase its price if consumers appreciate its unobserved attributes. Thus, ignoring such a firm's profit maximization behavior leads to a bias in the estimation of α. To address this endogeneity issue, following the literature, we use an IV approach. For our identification strategy, we use the variations in fuel prices and automobile prices induced by the changes in Korean policies such as the Clean Diesel policy and change in fuel taxes.

We use IVs as is usual in demand estimation models such as Berry, Levinsohn and Pakes 1995's model used in this study. Following Berry, Levinsohn and Pakes 1995, we use two typical instruments, namely, product characteristics and average attributes of the products manufactured by other firms. We also use the vehicle attributes of driving cost, length, width, size, and riding capacity, which are used in the literature as variables correlated with car prices but not with the other parts of the demand equation. For the fixed effects of the demand estimation, we add brand and year dummy variables.

Equation (6) shows that this computation requires evaluating a multidimensional integral in contrast to a traditional logit model that has a closed-form solution to compute the market share. To compute the market share (and parameter ξ), we therefore follow the standard method developed by Berry, Levinsohn and Pakes 1995 and Berry 1994. The moment property that we exploit in Equation (6) is that $E[\xi|z] = 0$, where z is the vector of the aforementioned instruments for each product j and the parameters are estimated using the two-step efficient generalized method of moments.[8]

4 Results

4.1 Demand Estimations

Table 2 shows the estimation results for eight model specifications. Models (1) and (2) are logistic OLS regressions. In Models (3) and (4), we run IV regressions with automobile prices as the IV. Finally, in Models (5) to (8), we estimate random coefficients for automobile prices with IV, and driving costs. In Models (1), (3), and (5), we assume that consumer preferences

[8] As this method is widely used in the literature, we do not repeat the details of the estimation procedure here to save space. This method computes the market share using aggregation by simulation methods to transform the observed market share and back out the estimated mean utility, based on which the parameters can be directly estimated. See Berry, Levinsohn and Pakes 1995 and Berry 1994 for the details.

for driving costs change annually. On the contrary, in Models (2), (4), and (6), we assume that consumer preferences for driving costs change quarterly. We thus focus on Model (6), as it is the fully specified model with quarterly changing driving costs. Finally, Models (7) and (8) include the lagged price terms of automobile price and driving costs. Model (7) does not include the quarterly interaction terms unlike Model (8). We include lagged automobile prices and driving costs in Models (7) and (8) because consumers make their purchasing decisions based on past observations of fuel prices given vehicle prices change little.[9] We include Models (7) and (8) to confirm the main results from Models (5) and (6).

Our first result from the estimation results for Models (2), (4), and (6) in Table 2 is that preferences for driving costs in Korea increased until 2017Q4, but decreased from 2018Q1. For example, the driving cost coefficient in 2017Q3 in Model (6) is the summation of the base (quarter) driving cost coefficient and driving cost coefficient in 2017Q3, which is $(-3.857) + (0.076)$. Similarly, the driving cost coefficient of 2018Q2 is $(-3.857) + (-0.725)$. Given that the dependent variable of the models is people's utility when deciding on a car purchase, a higher driving cost coefficient indicates that consumer preferences for fuel economy increase or that they become less sensitive towards the increase of the fuel costs; therefore, the reduction in utility is smaller than for consumers with lower driving cost coefficients. On the contrary, a lower driving cost coefficient indicates that an increase in fuel costs decreases people's utility relatively more.

In that sense, we find that the driving cost preference coefficients from 2018Q1 are much lower than the same coefficients from 2017Q4 for two possible reasons. First, driving cost preferences follow oil price trends. That is, both the policies in Phase 2 and the increase in both gasoline and diesel fuel costs around 2018Q1 lead to a large decrease in the coefficient from 2017Q4 to 2018Q1, indicating that consumers are becoming more sensitive toward the

[9] For example, from 2017Q1 to 2017Q4, the mean automobile price was 28.93 million KRW, compared with 28.96 million KRW from 2018Q1 to 2018Q4. We thank a referee for pointing this out. Hence, we still include lagged automobile prices to catch such small differences, and also because we acknowledge that automobile price is a crucial factor influencing the consumer's purchasing behaviors

increase in fuel costs than before. Furthermore, given that our data have a relatively short timespan and that the fuel economy improvements are insignificant, we assume that the changes in driving cost preferences are mostly induced by fuel cost changes.

Second, the change in driving cost preferences is correlated with policy-led automobile price changes. Driving costs fall when the Clean Diesel policy is abolished (2017Q4) (i.e., when fewer incentives are given to consumers to purchase diesel cars). Given that diesel cars have lower fuel economy than gasoline cars and HEVs, the increase in average fuel economy (due to the reduction of diesel cars sales) is likely to decrease the driving cost coefficient. We also confirm that the driving cost preference decreases the most in 2018Q4 when the diesel fuel price rises because of governmental policy.

The random coefficient results in Models (5) and (6) show a statistically significant level of heterogeneity in automobile prices and driving costs. Previous research typically finds heterogeneity among price coefficients (Tran and Winston 2007, Beresteanu and Li 2011). Given that the random coefficients are statistically significant and that these parameters help alleviate the well-known problem of independence of irrelevant alternatives shown by traditional logit models, the random coefficients play a critical role in defining the substitution patterns, as explained by Xing et al. 2018. We also find that the random coefficient of driving costs is larger than that of automobile prices in Models (5) and (6). One might think that consumers are more sensitive toward automobile prices, as the mean coefficient of automobile prices is much lower (-10.16 in Model (6)) than the driving cost coefficient (-3.857 in Model (6)). However, owing to the sizable individual heterogeneity in driving costs, we cannot simply conclude that driving costs contribute less than automobile prices to consumer demand for automobiles.

Third, Models (7) and (8) show that our results are qualitatively similar even after including lagged price terms, namely, one-quarter-lagged automobile prices and one-quarter-lagged driving costs. We thus show that these results are robust even after the inclusion of past price and cost terms. We also find that lagged automobile prices yield a negative coefficient and lagged driving costs a positive coefficient, showing that consumers are more sensitive toward automobile prices in the last quarter than fuel costs.

As expected, other vehicle attributes such as weight, length, and minivan status have positive and mostly statistically significant coefficients, implying that Korean consumers value these characteristics.

In summary, our demand estimation shows the importance of considering consumer preferences for fuel costs. However, if the Korean government adjusts fuel costs through policy instruments, will demand for automobiles change? More specifically, do fuel cost adjustments and consumer preferences affect consumers' choice of automobile fuel types and fuel economy? We answer these questions using a scenario analysis and by calculating the emissions of each hypothetical scenario in Section 4.3.

4.2 Robustness Checks

Before presenting our counterfactual simulations, we conduct multiple robustness checks to ensure that our estimates and implications are robust. We re-estimate some of the models above, allowing quarter-specific preferences for prices and vehicle weights after excluding quarter-specific preferences for driving costs. If there is a decreasing trend in vehicle weight, our main result is likely to be correlated with the other vehicle attributes (e.g., a high vehicle weight is likely to be correlated with lower fuel economy). We model three specifications. In Model (1), we use the logit specification. In Model (2), we apply a logit specification with the same IVs as in Section 4.1. In Model (3), we add the random coefficients of automobile price and driving cost from Model (2). Because our main model in Table 2 has random coefficients, we also focus on Model (3) here. As shown in Table 3, we mostly find no statistically significant differences except for in Model (1) that does not use IVs. However, a logit specification without an IV might lead to misleading interpretations, as shown by

Table 2: Demand Estimation Results

	Model (1) OLS Logit	Model (2) OLS Logit	Model (3) IV Logit	Model (4) IV Logit	Model (5) IV RC Logit	Model (6) IV RC Logit	Model (7) IV RC Logit	Model (8) IV RC Logit
ln(Automobile Price)	-2.096***	-2.093***	-4.160***	-4.133***	-9.851***	-10.16***	-9.767***	-9.833****
	(0.117)	(0.117)	(1.058)	(1.069)	(1.067)	(1.118)	(1.115)	(1.540)
ln(Driving Cost: Base)	-0.618***	-0.579***	-0.681***	-0.639***	-4.049***	-3.857***	-3.835***	-3.821***
	(0.111)	(0.110)	(0.121)	(0.119)	(0.122)	(0.120)	(0.129)	(0.126)
ln(Driving Cost: 2018)	0.120		-0.130		-0.728***		-0.873***	
	(0.133)		(0.190)		(0.191)		(0.191)	
ln(Driving Cost: 2017Q2)		0.049*		0.056*		0.202***		0.347***
		(0.028)		(0.030)		(0.030)		(0.042)
ln(Driving Cost: 2017Q3)		0.027		0.030		0.076**		0.030
		(0.028)		(0.030)		(0.030)		(0.034)
ln(Driving Cost: 2017Q4)		0.066**		0.067**		0.115***		0.058*
		(0.028)		(0.029)		(0.030)		(0.034)
ln(Driving Cost: 2018Q1)		0.147		-0.106		-0.872***		-0.669***
		(0.135)		(0.191)		(0.193)		(0.194)
ln(Driving Cost: 2018Q2)		0.159		-0.094		-0.725***		-0.551***
		(0.135)		(0.191)		(0.193)		(0.193)
ln(Driving Cost: 2018Q3)		0.145		-0.107		-0.859***		-0.788***
		(0.135)		(0.191)		(0.192)		(0.193)
ln(Driving Cost: 2018Q4)		0.189		-0.060		-0.654***		-0.577***
		(0.136)		(0.190)		(0.192)		(0.192)
Minivans	2.092***	2.085***	2.204***	2.196***	1.359***	1.376***	1.420***	1.386***
	(0.299)	(0.300)	(0.318)	(0.318)	(0.320)	(0.320)	(0.331)	(0.330)
Small Cars	-2.538***	-2.568***	-1.206	-1.254	-2.034**	-2.086**	-1.683*	-1.907*
	(0.645)	(0.646)	(0.957)	(0.956)	(0.965)	(0.962)	(0.987)	(0.984)
Riding Capacity	0.172	0.168	0.168	0.164	0.994***	1.033***	0.947***	0.949***
	(0.247)	(0.247)	(0.258)	(0.258)	(0.259)	(0.259)	(0.270)	(0.270)
Weight (kg)	3.884***	3.904***	7.635***	7.611***	10.22***	10.34***	10.17***	10.25***
	(0.362)	(0.362)	(1.947)	(1.946)	(1.967)	(1.963)	(2.043)	(2.039)
Car Length (mm)	2.714***	2.659***	2.708***	2.652***	-1.814**	-1.906**	-1.506*	-1.596*
	(0.773)	(0.773)	(0.808)	(0.808)	(0.813)	(0.811)	(0.844)	(0.842)
Random Coeff. of Automobile Price					1.794***	1.881***	1.750***	1.762***
					(0.413)	(0.583)	(0.421)	(0.562)
Random Coeff. of Driving Cost					3.420***	3.419***	3.222***	3.311***
					(0.927)	(0.902)	(0.915)	(0.898)
Lagged Automobile Price							-0.599***	-0.102
(Lag: 1 quarter)							(0.126)	(0.103)
Lagged Driving Cost							1.945***	0.521**
(Lag: 1 quarter)							(0.214)	(0.155)
Constant	-24.58***	-24.70***	-35.81***	-35.88**	-35.69***	-35.16***	-35.13***	-35.13***
	(1.839)	(1.840)	(6.048)	(6.091)	(7.007)	(6.979)	(7.302)	(7.668)
Fixed Effects (FE)								
Brand FE	√	√	√	√	√	√	√	√
Year FE	√	√	√	√	√	√	√	√
N	3,302	3,302	3,302	3,302	3,302	3,302	3,302	3,302
R^2	0.145	0.143	0.064	0.064	0.683	0.670	0.671	0.666

Note: Standard errors are shown in parentheses. + p<0.1; * p<0.05; ** p<0.01; *** p<0.001.

Berry, Levinsohn and Pakes 1995, because of unobserved characteristics. Therefore, more attention should be paid to Model (3). Thus, we can conclude that our findings are robust, as we confirm that consumer preferences for vehicle weight did not change over time. This confirms our findings in Table 2.

Table 3: Robustness Test Results

	Model (1) Logit	Model (2) IV Logit	Model (3) IV RC Logit
ln(Automobile Price)	-2.308***	-0.507	-12.17***
	(0.310)	(2.855)	(2.953)
ln(Driving Cost: Base)	-0.488***	-0.479***	-1.076***
	(0.077)	(0.079)	(0.079)
Weight	7.757***	3.918***	-1.533
	(3.677)	(1.085)	(20.75)
Weight : 2017Q2	0.281	2.030	1.500
	(0.444)	(2.793)	(2.888)
Weight : 2017Q3	0.357	2.107	1.524
	(0.446)	(2.793)	(2.888)
Weight : 2017Q4	0.448	2.211	1.490
	(0.454)	(2.816)	(2.911)
Weight : 2018Q1	-0.564	1.764	0.596
	(0.627)	(3.721)	(3.848)
Weight : 2018Q2	-1.346**	0.994	-0.054
	(0.623)	(3.721)	(3.867)
Weight : 2018Q3	-0.961	1.380	0.649
	(0.624)	(3.741)	(3.868)
Weight : 2018Q4	-1.431**	0.915	0.198
	(0.599)	(3.745)	(3.872)
Minivans	2.099***	2.024***	1.657***
	(0.299)	(0.323)	(0.327)
Small Cars	-2.308***	-0.507	-2.587***
	(0.310)	(2.855)	(0.972)
Riding Capacity	0.146	0.135	1.041***
	(0.246)	(0.248)	(0.250)
Car Length (mm)	2.707***	2.621***	1.140
	(0.775)	(0.790)	(0.797)
Random Coeff. of Automobile Price			3.674
			(24.88)
Random Coeff. of Driving Cost			2.712
			(3.323)
Constant	-29.68**	-26.26***	-20.63***
	(2.205)	(5.823)	(6.002)
Fixed Effects (FE)			
Brand FE	✓	✓	✓
Year FE	✓	✓	✓
Price Interaction	✓	✓	✓
N	3,302	3,302	3,302
R^2	0.149	0.140	0.884

Note: Standard errors are shown in parentheses. + p<0.1; * p<0.05; ** p<0.01; *** p<0.001.

Second, we verify the fit of our demand model by simulating, for each quarter, the situation that consumers choose their automobiles in that quarter again. We do so to ensure that our demand model can replicate consumers' behavior, thereby allowing us to run the counterfactual simulations. Table 4 shows the results of the fitness test of each quarter and year. Here, "Data" refers to the actual sales value in our data and "Simulation" shows the simulation results. In the "% Difference" column, we also calculate the percentage difference between the actual data and simulation values. The results show that the difference is less than 10% and seems to be driven mainly by the random coefficients in Table 2. The difference between the data and simulation values fluctuate between positive and negative values, indicating randomness in the bootstrap simulations. Further, as we find a good fit for both models (with quarters and with years), we select years for the counterfactual simulations, as those results provide long-term implications. We discuss this further in Section 4.3.

Table 4: Fit of the Model

Quarter	Data	Simulation	% Difference	Bootstrap p value	95% Confidence Interval
2017Q1	341,757	352,039	3.01%	0.000***	321,605.2 – 361,908.8
2017Q2	385,923	353,476	-8.41%	0.000***	322,327.6 – 449,518.4
2017Q3	355,362	352,493	-0.81%	0.000***	349,739.5 – 360,984.5
2017Q4	363,866	352,695	-3.07%	0.000***	341,971.9 – 385,760.1
2018Q1	343,326	357,619	4.16%	0.000***	315,311.6 – 371,340.4
2018Q2	385,676	358,851	6.96%	0.000***	333,099.6 – 438,252.4
2018Q3	352,306	357,824	1.64%	0.000***	341,491.3 – 363,120.7
2018Q4	394,514	359,076	-0.90%	0.000***	325,057.2 – 463,970.8
Year	**Data**	**Simulation**	**% Difference**	**Bootstrap p value**	**95% Confidence Interval**
2017	1,446,908	1,410,703	-2.50%	0.000***	1,375,948 – 1,517,868
2018	1,475,552	1,433,370	-2.86%	0.000***	1,392,877 – 1,558,227

Note: The fourth column, % Difference, is calculated as 100*(Data - Simulation)/Data.

4.3 Counterfactual Simulations

4.3.1 Scenario Settings

Based on the demand estimation results, we find that automobile price, fuel cost, and time-varying driving cost preferences are all crucial in determining automobile demand. Furthermore, the random coefficient of driving costs is higher than that of automobile prices, while the mean coefficient of automobile prices is lower than that of driving costs. This suggests we should investigate which policy measures reduce diesel car demand the most, which is ambiguous from the demand estimation results alone. Thus, we use counterfactual simulations to quantify and decompose the impact of consumer preferences, fuel costs, and automobile prices on automobile sales and emissions.

The efficiency of policy measures critically depends on consumer preferences. For example, if consumers are highly sensitive toward fuel costs, they would not purchase less fuel-efficient cars regardless of the financial incentives. Conversely, if consumers are less sensitive toward fuel costs, financial incentives would be unnecessary. On the contrary, if the policy impact on automobile demand is much larger than that on consumer preferences, the Korean government could design policies without having to consider substantially for consumer preferences.

Our hypothetical scenarios incorporate the periods in which consumers are both less sensitive and highly sensitive toward fuel costs to investigate how policies change consumers' car choices. We further examine whether consumers are more sensitive to automobile prices or fuel costs, as both these variables differ based on their random coefficients.

As mentioned in Section 2.2, the two Korean policies had different goals. The Clean Diesel Act was abolished to decrease emissions from diesel cars, whereas diesel prices were reduced to boost employment. Given that the Korean government implemented these two contrasting policies at roughly the same time, we separate the effects of fuel tax changes and car price changes by simulating from these scenarios.

To this end, we set two main scenarios. In Scenario 1, we hypothetically take consumers from 2018Q4 and give them the vehicle choice set from 2017Q1. In Scenario 2, we hypothetically give consumers from 2017Q1 the choice set of the automobiles available in 2018Q4. To determine the policy implications, we simulate two additional scenarios for each of these main scenarios. In Scenarios 1-a and 2-a, we test the impact of an additional 10% diesel fuel tax. In Scenarios 1-b and 2-b, we examine the effect of increasing the price of diesel automobiles by another 10%.

Table 5 summarizes our scenario exercises. The upper panel describes our scenarios and the lower panel presents their main objective. Given that consumers in 2017Q1 and 2018Q4 face the abolition of both diesel price subsidies and diesel car subsidies, we mark them as "Contrasting Policies." For Scenarios 1-a and 2-a, as we change the fuel tax rate in addition to Scenario 1, we mark them as "Fuel Tax Change" with "Contrasting Policies." Similarly, as we increase the diesel car price and contrasting policies in Scenario 1-b and 2-b, we mark them as "Automobile Price Change" and "Contrasting Policies."

In this simulation, we do not take technological advancement into account, as we examine a relatively short period of two years. Therefore, the simulation results should allow us to disentangle the impacts of consumer preferences and policies. The results of these simulations are meaningful to policymakers in two ways. First, as rapid technological advancement is not expected to have occurred in such a short period, our simulation results provide evidence on whether consumer preferences are more critical than policy in controlling emissions. Second, as the marginal amount of technological advancement decreases over time—or its costs increase—consumer preferences or policies become increasingly important factors in affecting emissions. In addition, consumers in 2017Q1 have different fuel cost preferences than consumers in 2018Q4. As these two quarters consist of different sets of consumers, we should exercise caution in interpreting the results of these counterfactual scenarios.

Table 5: Scenario Descriptions

Scenario	**Descriptions**
Scenario 1	Hypothetically Take People from 2018Q4 to 2017Q1
Scenario 1-a	Scenario 1 + 10% Increase in Diesel Fuel Tax
Scenario 1-b	Scenario 1 + 10% Increase in Diesel Car Prices
Scenario 2	Hypothetically Take People from 2017Q1 to 2018Q4
Scenario 2-a	Scenario 2 + 10% Increase in Diesel Fuel Tax
Scenario 2-b	Scenario 2 + 10% Increase in Diesel Car Prices

Scenario	**Contrasting Policies**	**Fuel Tax Change**	**Automobile Price Change**
Scenario 1	O	X	X
Scenario 1-a	O	O	X
Scenario 1-b	O	X	O
Scenario 2	O	X	X
Scenario 2-a	O	O	X
Scenario 2-b	O	X	O

4.4 Simulation Results

To focus on the changes in consumer preferences in the longer term, we examine yearly instead of quarterly differences. While quarterly differences may be more prone to seasonal or stochastic changes in consumer preferences, if any exist, using yearly differences more clearly shows the differences in preferences over time. Furthermore, when interpreting the results, we focus on diesel automobile sales, as we evaluate policies that directly influence diesel car sales and emissions.

Table 6 shows the simulation results, with automobile sales (Panel (A)), fuel economy (Panel (B)), and the number of cars sold by fuel type ((Panels (C) and (D)). "Preference" refers to the time of consumer preferences taken as a benchmark and "Fuel Costs" shows the time of fuel costs taken as a benchmark. "Data" refers to the original data and "Simulation" shows the projected values. "Difference" shows the differences between the simulated values and data.

First, when we take strongly fuel price-sensitive consumers from 2018Q4 and present them with the automobile choices from 2017Q1 (Scenario 1), we observe that sales decrease by 3.04%, mainly because consumers in 2018Q4 are more fuel price-sensitive; thus, they do not buy cars in 2017Q1 because the fuel costs in this quarter are higher than those in 2018Q4.

Second, when we take less fuel price-sensitive consumers from 2017Q1 to 2018Q4 (Scenario 2), sales increase by 3.20% because consumers in 2017Q1 are not as fuel price-sensitive as consumers in 2018Q4. Therefore, consumers from 2017Q1 are willing to purchase a new car or replace their existing one, as fuel costs in 2018Q4 are cheaper than those in 2017Q1.

Specifically, in Panel (A) in Table 6, if we increase the diesel fuel tax by 10% (Scenario 1-a), automobile sales decrease slightly, by 4.86%. Increasing diesel car prices by 10% (Scenario 1-b) decreases automobile sales by 6.48%. Compared with Scenario 1, Scenarios 1-a and 1-b result in fewer automobiles being sold, indicating that the policy effects can be amplified by fuel cost-sensitive consumers. We also find that increasing diesel automobile prices is more effective at reducing vehicle sales than increasing diesel prices.

Increasing the price of automobiles decreases sales; however, if consumers are not sensitive toward fuel costs, higher automobile prices alone cannot reduce sales of automobiles. We confirm that automobile sales increase by 2.13% if we increase the diesel fuel tax by 10% (Scenario 2-a), which is a smaller increase than in Scenario 2. Alternatively, if we increase diesel car prices by 10% (Scenario 2-b), automobile sales still increase but only by 0.54%, indicating that compared with Scenarios 2 and 2-a, increasing diesel car prices decreases sales even though consumers are more willing to purchase cars when fuel prices are lower.

Panel (B) shows the sales-weighted average fuel economy in each scenario. Compared with Panel (A), we do not find significant changes in fuel economy except for in Scenario 2. This result indicates that Korean consumers are not likely to choose cars based on fuel economy.

To further understand how these consumers change their purchasing patterns, we also calculate the changes in demand by car fuel type. We focus on gasoline and hybrid cars (Panel

(C)) and diesel cars (Panel (D)).[10] We calculate the difference of the obtained numbers from the data and compute the market share of each type.

First, we find that increasing both the cost of diesel and diesel car prices would incentivize people to prefer gasoline and hybrid cars over diesel cars. We confirm that increasing diesel car prices has a substantial impact on diesel car demand. For example, in Scenarios 1-b and 2-b, the market share of gasoline cars and HEVs increases substantially, while that of diesel cars decreases significantly. Second, increasing diesel prices encourages consumers to choose gasoline cars and HEVs over diesel cars, while the magnitude is smaller than that of diesel cars.

Further, relative to Scenario 1, the market shares for gasoline cars and HEVs are smaller in Scenario 1-a and greater in Scenario 1-b. The market share for diesel cars is greater in Scenario 1 than in the data because diesel-fueled automobiles are less expensive than gasoline cars and the diesel cost is cheaper than the gasoline, which attracts more consumers toward them. By contrast, the market share for diesel cars is greater in Scenario 1 than in Scenario 1-a and smaller in Scenario 1-b.

On the contrary, our results suggest that when consumers are less fuel cost-sensitive (Scenario 2), they replace diesel cars with gasoline and hybrid vehicles. Scenarios 2, 2-a, and 2-b show that the market shares of gasoline and hybrid vehicles increase, whereas that of diesel cars decreases. Moreover, relative to Scenario 2, the combined market share for gasoline cars and HEVs is higher in Scenarios 2-a and 2-b, whereas that for diesel cars is smaller.

We conclude that controlling demand for diesel cars relies on consumer preferences. That is, Korean consumers are unlikely to purchase vehicles according to their fuel economy and prioritize fuel costs and automobile prices. When fuel costs are higher and consumers are

[10]We also acknowledge that demand for LPG cars and EVs changes but found no significant substitution patterns for these two types of automobiles. Specifically, sales of EVs and LPG cars decrease in Scenarios 1, 1-a, and 1-b and increase in Scenarios 2, 2-a, and 2-b.

less fuel cost-sensitive, they are instead more likely to substitute gasoline and hybrid cars with diesel cars. Diesel cars' fuel costs are the cheapest, while diesel's fuel economy is the lowest.

Table 6: Simulation Results

	Preference	Fuel Cost	Data	Simulation	Difference
(A): Automobile Sales					
Data	2017Q1	2017Q1	1,446,908		
Scenario 1	2018Q4	2017Q1		1,402,869	-3.04%
Scenario 1-a	2018Q4	2017Q1		1,376,540	-4.86%
Scenario 1-b	2018Q4	2017Q1		1,353,158	-6.48%
Data	2018Q4	2018Q4	1,475,552		
Scenario 2	2017Q1	2018Q4		1,522,754	3.20%
Scenario 2-a	2017Q1	2018Q4		1,506,971	2.13%
Scenario 2-b	2017Q1	2018Q4		1,483,576	0.54%
(B): Fuel Economy (km/l)					
Data	2017Q1	2017Q1	12.35		
Scenario 1	2018Q4	2017Q1		12.22	-1.07%
Scenario 1-a	2018Q4	2017Q1		12.28	-0.06%
Scenario 1-b	2018Q4	2017Q1		12.12	-1.92%
Data	2018Q4	2018Q4	12.21		
Scenario 2	2017Q1	2018Q4		11.20	-8.20%
Scenario 2-a	2017Q1	2018Q4		12.24	-0.32%
Scenario 2-b	2017Q1	2018Q4		12.47	0.31%

(C): Gasoline + HEV cars sold		Difference	Market Share
Data	747,012		51.63%
Fitted Value	732,255	-16.18%	50.60%
Scenario 1	722,683	-17.96%	51.51%
Scenario 1-a	778,515	-12.53%	56.55%
Scenario 1-b	943,884	26.35%	69.75%
Data	773,617		52.43%
Fitted Value	763,382	-1.32%	51.74%
Scenario 2	830,113	7.30%	54.51%
Scenario 2-a	872,891	12.83%	57.92%
Scenario 2-b	1,045,307	35.12%	70.45%

(D): Diesel cars sold		Difference	Market Share
Data	564,756		39.03%
Fitted Value	552,195	-2.23%	38.16%
Scenario 1	560,786	-0.70%	39.97%
Scenario 1-a	471,899	-16.44%	34.28%
Scenario 1-b	263,068	-53.42%	19.44%
Data	567,884		38.48%
Fitted Value	563,369	-0.80%	33.23%
Scenario 2	583,304	2.72%	38.31%
Scenario 2-a	512,876	-9.69%	34.03%
Scenario 2-b	288,866	-49.13%	19.47%

Note: As in Table 4, we also conduct bootstrap tests and confirm that our fitted value is significant at $p > 0.05$ and within the confidence interval range. See Appendix Table A1 for the detailed results.

4.5 Consequences in Terms of Emissions

Based on the results in Table 6, we calculate diverse emissions of the car market in each scenario, notably emissions of Carbon Dioxide (CO_2), Nitrogen Oxide (NOx), and Particulate Matter (PM). The calculated emissions here are figures for after the purchases of new cars rather than overall emissions from all vehicles. To calculate emissions, we let the fuel usage of automobile j in year t equal the inverse of fuel economy in liters per kilometer following Yoo, Wakamori and Yoshida 2019 and Clerides and Zachariadis, 2008. Emissions at time t, TE_t, can be calculated by multiplying sales, $Q_{j,t}$, by driving distance, $D_{j,t}$, and fuel usage, $FU_{j,t}$. Therefore, aggregate emissions can be calculated as

$$TE_t = \sum_j FU_{j,t} \cdot D_{j,t} \cdot Q_{j,t} \cdot A,$$

where A denotes the emissions calculation factor and $D_{j,t}$ denotes the driving distance of automobile j in year t. A differs by automobile fuel type, namely, gasoline (including hybrid vehicles), diesel, LPG, and electricity (for EVs). In regards to CO_2 emissions, diesel emits the largest amount (2.6 kg/l), followed by gasoline (2.4 kg/l) and LPG (1.7 kg/l). In terms of NOx emissions, diesel also emits the largest amount (0.8 g/l), followed by gasoline (0.5 g/l) and LPG (0.16 g/l)[11]. As PM is only calculated for diesel cars (3.8 mg/l), the emissions amount primarily reflects car type substitutions.

Table 7 displays the values used for our simulation analysis. As gasoline, HEV, and LPG cars do not emit PM, we do not include their PM emissions values in the table. The emission calculation factors represent emissions for each 1 liter of consumption. The units are as follows: Ton eq for CO_2 and kg eq for NOx and PM. For example, consuming 1 liter of gasoline results in 2.3 kg of CO_2 and 0.005 kg of NOx. Among all fuel types, the diesel

[11] We acknowledge that NOx emissions depend on engine type. Thus, we use the average NOx emission factor of average passenger cars published by the National Institute for Land and Infrastructure Management in Japan.

emission calculation factors are the highest.

Table 7: Values Used for the Simulations

Fuel Type	Gasoline and HEV	Diesel	LPG
Yearly Travel Distance (km)	11,169	17,118.5	17,593
Fuel Usages (l/km)	0.090	0.075	0.115
Emission Calculation Factor (CO_2)	0.0023	0.0026	0.0023
Emission Calculation Factor (NOx)	0.005	0.008	0.005
Emission Calculation Factor (PM)		0.005	
N	1,692	1,008	314

EVs are excluded from the simulations, as they do not have emissions.

Table 8 provides the results from the emissions simulations. Each panel represents CO_2, NOx, and PM emissions, "Preference" refers to the time of consumer preferences taken as a benchmark and "Fuel Costs" shows the time of fuel costs taken as a benchmark. "Data" refers to the original data and "Simulation" shows projected emissions. "Difference" shows the differences between the simulated emissions and data.

The emissions in Panels (A), (B) and (C) show a decreasing trend in general. Compared with CO_2 and NOx emissions, which are emitted from gasoline, LPG, and diesel cars, PM emissions only come from diesel cars. First, we find that emissions are lower in Scenarios 1, 1-a, and 1-b and the lowest in Scenario 1-b regardless of emission type. This is because fuel cost-sensitive people of 2018Q4 are unlikely to purchase cars in 2017Q1 and the magnitude rises if the fuel cost increases (Scenario 1-a) as well as if the diesel car price increases (Scenario 1-b).

Second, unlike Scenario 1, emissions are higher in Scenario 2, as people in 2017Q1 are sensitive toward fuel costs and purchase cars in 2018Q4 because of the cheaper fuel costs. However, emissions mostly decrease compared with Scenario 2 if the diesel price is increased (Scenario 2-a) and diesel car price is increased (Scenario 2-b). PM emissions show the largest decline over CO_2 and NOx because PM emissions solely depend on the number of diesel cars sold, which has decreased, as seen in Panels (C) and (D) in Table 6.

Table 8: Emissions Simulation Results

	Preference	Fuel Costs	Data	Simulation	Difference
(A): CO_2 Emissions (Million tons eq)					
Data	2017Q1	2017Q1	4.17		
Fitted Value	2017Q1	2017Q1		4.12	-1.22%
Scenario 1	2018Q4	2017Q1		4.10	-1.79%
Scenario 1-a	2018Q4	2017Q1		3.89	-6.70%
Scenario 1-b	2018Q4	2017Q1		3.62	-13.08%
Data	2018Q4	2018Q4	4.22		
Fitted Value	2017Q1	2018Q4		4.19	-0.55%
Scenario 2	2017Q1	2018Q4		4.52	7.16%
Scenario 2-a	2017Q1	2018Q4		4.27	1.19%
Scenario 2-b	2017Q1	2018Q4		3.81	-9.52%
(B): NOx Emissions (Thousands kg eq)					
Data	2017Q1	2017Q1	1,035.19		
Fitted Value	2017Q1	2017Q1		1,019.08	-1.55%
Scenario 1	2018Q4	2017Q1		1,017.33	-1.72%
Scenario 1-a	2018Q4	2017Q1		937.96	-9.39%
Scenario 1-b	2018Q4	2017Q1		897.82	-13.31%
Data	2018Q4	2018Q4	1,054.96		
Fitted Value	2017Q1	2018Q4		1,047.33	-0.07%
Scenario 2	2017Q1	2018Q4		1,125.99	6.73%
Scenario 2-a	2017Q1	2018Q4		1,038.99	-1.51%
Scenario 2-b	2017Q1	2018Q4		948.22	-10.12%
(C): PM (Thousands kg eq)					
Data	2017Q1	2017Q1	3.17		
Fitted Value	2017Q1	2017Q1		3.10	-2.20%
Scenario 1	2018Q4	2017Q1		3.11	-1.90%
Scenario 1-a	2018Q4	2017Q1		2.61	-17.84%
Scenario 1-b	2018Q4	2017Q1		1.47	-53.84%
Data	2018Q4	2018Q4	3.23		
Fitted Value	2017Q1	2018Q4		3.19	-1.12%
Scenario 2	2017Q1	2018Q4		3.38	4.59%
Scenario 2-a	2017Q1	2018Q4		2.92	-9.51%
Scenario 2-b	2017Q1	2018Q4		1.64	-49.35%

To derive more implications, we examine the emissions from different fuel types. Panel (A) of Table 9 shows emissions from gasoline and hybrid cars and Panel (B) shows emissions from diesel cars. While we find mostly similar implications to in Table 8, two points are worth highlighting. First, diesel cars produce more emissions than gasoline and hybrids regardless of emission type, mainly due to their low fuel economy. Second, our result implies that adjusting diesel car prices may not lead to emissions reductions. We find that increasing diesel car prices (Scenarios 1-b and 2-b) may lead to an increase in gasoline car emissions.

For example, CO_2 and NOx emissions in Scenario 1-b are higher than in Scenarios 1 and 1-a. Similarly, emissions in Scenario 2-b show no significant reductions compared with Scenario 2 or 2-a. This result indicates that people may substitute diesel with gasoline cars, increasing the market share of gasoline and hybrid cars.

Table 9: Emissions from Cars with Different Fuel Types

(A): Emissions from Gasoline + HEV Cars			
	CO_2	NOx	PM
Data	1.59	332.34	0
Scenario 1	1.58	328.56	0
Scenario 1-a	1.69	352.81	0
Scenario 1-b	2.13	443.89	0
Data	1.66	346.13	0
Scenario 2	1.85	384.68	0
Scenario 2-a	1.87	389.62	0
Scenario 2-b	2.20	458.25	0
(B): Emissions From Diesel Cars			
	CO_2	NOx	PM
Data	2.16	663.16	3.15
Scenario 1	2.11	650.54	3.11
Scenario 1-a	1.77	544.84	2.61
Scenario 1-b	1.00	306.08	1.47
Data	2.19	674.87	3.18
Scenario 2	2.29	705.86	3.38
Scenario 2-a	1.98	610.69	2.92
Scenario 2-b	1.11	341.79	1.64

Note: All the results are in the same units as in Table 8.

4.6 Comparison between Scenarios

We find that the contrasting set of Korean policies may lead to unexpected outcomes. In particular, Scenario 2 shows an increase in CO_2 emissions from the data because of a rise in automobile sales. Scenario 1 also shows a smaller reduction in emissions than Scenarios 1-a and 1-b.

Further, there is a proportional change in emissions between Scenarios 1, 1-a and 1-b and Scenarios 2, 2-a, and 2-b. That is, increasing diesel prices (Scenarios 1-a and Scenario 2-a) reduces the number of diesel cars sold and emissions from diesel cars compared with the no-policy scenarios (Scenarios 1 and 2). When the diesel car price is increased (Scenarios 1-b and 2-b), the number of diesel cars sold and emissions from diesel cars decrease more than in Scenarios 1-a and 2-a. However, this result does not indicate that policies focused on fuel costs are futile, as raising the fuel tax would not increase government expenditure and still reduce emissions. For instance, Scenarios 1-a and 2-a always show reduced emissions and automobile sales as well as increased fuel economy compared with Scenarios 1 and 2.

The policies can achieve more emissions reductions when faced with fuel cost-sensitive consumers than those who are not sensitive toward fuel costs. We see more reductions in automobile sales and emissions in Scenarios 1, 1-a, and 1-b than in Scenarios 2, 2-a, and 2-b in the same setting. For example, if the diesel price increases by 10%, Scenario 1-a shows a 6.70% reduction in CO_2 emissions followed by an automobile sales drop of 4.86% and fuel economy reduction of 0.06%, while Scenario 2-a shows an increase in CO_2 emissions of 1.19% followed by an automobile sales increase of 2.13% and fuel economy decrease of 0.32%.

In sum, our results highlight that consumer preferences and policies are highly correlated with automobile demand and emissions, as our results indicate that consumer preferences can amplify (or reduce) the policy impacts on automobile sales and emissions. We also confirm that to reduce emissions from diesel cars, it would be more useful to increase diesel car prices than increase diesel fuel costs. Here, increasing the diesel car price implies, among other policy measures, the reduction of diesel car subsidies, which makes consumers consider diesel cars to be more expensive. In other words, this is the abolition of the Clean Diesel policy in this study rather than governmental intervention to directly alter car prices.

4.7 Policy Implications

We find that emissions do change according to consumer preferences and policy instruments. First, when consumers are sensitive toward fuel costs, automobile sales decrease, and consequently emissions generally decrease. On the contrary, when consumers are less sensitive toward fuel costs, our results indicate that emissions decrease by less than, or even increase from, when consumers are more sensitive. The effect on emissions depends more on the number of automobiles than on fuel economy, as emissions are proportional to automobile sales (see Table 6).

Here, we treat fuel costs as a proxy for distance costs. It is worth highlighting why such a treatment works. We introduce the driving cost, instead of fuel cost, to consider the fuel economy choices of consumers. Many vehicle models in the Korean automobile market have a fuel economy from 4.4 km/l to 22.4 km/l. However, the sales-weighted average and average fuel economy did not show sizable changes during our study period. Specifically, both types of fuel economy were around 12 km/l from 2017Q1 to 2018Q4 (see Table A2), implying that the driving cost rests more on fuel costs than on fuel economy choices. Thus, we discuss our results in terms of the alternative terminology of 'fuel costs' as a proxy for 'driving cost'.

Second, we also conclude that the set of contrasting policies in Korea may not result in significant reductions in emissions. One would think that increasing diesel fuel costs would induce Korean consumers to purchase more fuel-efficient cars. However, we find that increasing the diesel fuel tax (Scenarios 1-a and 2-a) would not result in a significantly different outcome from the benchmark scenarios, as the changes in emissions and automobile sales are insignificant. To reduce emissions or sales of diesel automobiles, our results show that increasing the diesel car price by abolishing subsidies would be more effective than readjusting the diesel fuel tax.

These results also indicate that rather than implementing policies, improving the fuel economy of cars or raising environmental awareness (e.g., regarding the generally lower fuel economy of diesel cars than gasoline cars) could also provide a better solution for reducing overall emissions. Such approaches would provide a sustainable way of decreasing emissions in the future.

5 Conclusion

We answer the research question, “Do consumers abandon diesel automobiles due to contrasting diesel policies?” with “No, only those who are sensitive to fuel cost would do.” To reach that answer, we examine a contrasting set of energy policy changes, through which the Korean government has sought to reduce the emissions from the transportation sector by controlling the demand for diesel cars in 2017 and 2018. Our results from the demand estimation show that Korean consumers have become more sensitive toward fuel costs over time. Based on the obtained consumer preferences for driving costs, we run counterfactual simulations for the policies, followed by scenario analyses with different diesel fuel tax rates and diesel car prices. We conclude by comparing the emission levels obtained from the counterfactual simulations.

We find that governments should consider consumer preferences in addition to providing economic incentives. We suggest two avenues for future research. First, as this study focuses on policy changes over two years, expanding the period to, for example, 10 years or more would provide emissions implications for the long term. This would allow us to explore whether manufacturers have improved fuel economy, as adjusting fuel efficiency specifications (e.g., displacement and car weight) for each model is time consuming. Whether consumer preferences for fuel economy change with the introduction of new automobiles could also be examined in the long run. Furthermore, researchers could consider whether seasonal effects impact automobile demand in the longer term.

Second, endogenizing travel distance would provide important research results. We acknowledge that travel distance is endogenous and too complex to be measured simply. Consumers can change their driving patterns according to fuel prices and new car choices, or even opt for public transportation. Still, the results from examining these travel patterns, combined with our results and technological developments, could help reduce emissions and fuel usage more effectively in the long term.

Data Source

For the data sources, we take Korean monthly oil prices from www.opinet.co.kr, vehicle attributes from auto.danawa.com, travel distances from the Ministry of Land, Infrastructure and Transport (MoLIT)'s website at www.molit.go.kr. We also refer to changes in Korean automobile and fuel policies in 2018 from the MoLIT website and the Korean Automobile Association. (http://www.kama.or.kr/jsp/webzine/201801/pages/issue_02.jsp). Regarding the emssions factors, we refer to a material published in National Institute for Land and Infrastructure Management, Japan. (http://www.nilim.go.jp/lab/bcg/siryou/tnn/tnn0671pdf/ks067108.pdf)

Appendix

Table A1 shows the bootstrap test results for the simulations in Table 6 and 8. We find that all estimates have a statistically significant p value from bootstrap estimations.

Table A1: Bootstrap Simulation Results

(A): Gasoline + HEV cars sold			
		Bootstrap p value	Confidence Interval
Data (Year 2017)	747,012		
Fitted Value	732,255	0.00***	718,089.4 — 775,934.6
Data (Year 2018)	773,617		
Fitted Value	763,382	0.00***	753,556.2 — 793,677.8
(B): Diesel cars sold			
		Bootstrap p value	Confidence Interval
Data (Year 2017)	564,756		
Fitted Value	552,195	0.00***	540,066.5 — 589,445.5
Data (Year 2018)	567,884		
Fitted Value	563,369	0.00***	559,034.2 — 576,733.8
(C): CO_2 Emissions (Million tons eq)			
		Bootstrap p value	Confidence Interval
Data (Year 2017)	4.17		
Fitted Value	4.12	0.00***	4.07 — 4.27
Data (Year 2018)	4.22		
Fitted Value	4.19	0.00***	4.17 — 4.26
(D): NOx Emissions (Thousands Kg eq)			
		Bootstrap p value	Confidence Interval
Data (Year 2017)	1,035.19		
Fitted Value	1,019.08	0.00***	1,003.60 — 1,066.78
Data (Year 2018)	1,054.96		
Fitted Value	1,047.33	0.00***	1,040.00 — 1,069.91
(E): Particulate Matter (Thousands Kg eq)			
		Bootstrap p value	Confidence Interval
Data (Year 2017)	3.17		
Fitted Value	3.10	0.00***	3.03 —3.31
Data (Year 2018)	3.23		
Fitted Value	3.19	0.00***	3.16 — 3.30

Table A2 shows the sales weighted fuel economy level and average fuel economy levels by quarters. We confirm that there was not a significant change in sales-weighted average fuel economy.

Table A2: Summary of Sales-Weighted Average and Average Fuel Economy Levels by Quarter

Quarter	Sales-Weighted Average Fuel Economy (km/l)	Average Fuel Economy (km/l)
2017Q1	12.2	12.38
2017Q2	12.29	12.35
2017Q3	12.42	12.26
2017Q4	12.49	12.34
2018Q1	12.31	12.43
2018Q2	12.15	12.36
2018Q3	12.23	12.44
2018Q4	12.15	12.39

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