Energy Policy 109 (2017) 473–478

Contents lists available at ScienceDirect

Energy Policy

journal homepage: www.elsevier.com/locate/enpol

Impacts of renewables and socioeconomic factors on electric vehicle demands – Panel data studies across 14 countries

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ARTICLE INFO

Keywords:
Renewable energy
Electric vehicle demand
Socioeconomic factor

ABSTRACT

Electric vehicle demands have increased rapidly since 2010, and depend on renewables and socioeconomic factors. Using panel data from fourteen countries between 2010 and 2015, we study impacts of seven factors in a multiple linear regression model. The factors include percentage of renewable energies in electricity generation, number of charging stations, education level, population density, gasoline price, GDP per capita and urbanization. The first four factors have apparent and positive impacts on the demands, and the last two factors don't. The gasoline price affects the demands for BEVs (battery electric vehicles) more than that for PHEVs (plug-in hybrid electric vehicles). One percent increase in renewables would lead to approximately 2–6% increase in EV demands. Based on the results, policy implications are discussed.

1. Introduction

1.1. Renewables

Energy sustainability is a major challenge facing the entire world. Recently, EIA predicted that the average annual world energy consumption will increase approximately 40% in the next twenty three years or so (EIA U.S. Energy Information Administration, 2016). With fossil fuel being the main sources, carbon dioxide (CO_2) concentration may reach a threshold of 450 ppm equivalent (Calvin et al., 2009). At the present time, transportation sectors contribute approximately 23% of global energy-related CO_2 emissions (IEA International Energy Agency, 2015). Improving energy efficiencies may reduce total energy consumptions, and using EVs (electric vehicles) may reduce emissions locally. If EV batteries can be charged with electricity from renewables, the emissions can be substantially reduced for the entire life cycles of EVs (McLaren et al., 2016; Dias et al., 2014; Hennings et al., 2013; Weiller and Sioshansi, 2014). Presumably, more renewables will lead to higher EV demands due to following two reasons. 1. Consumers with environment awareness want electricity with renewables. As illustrated by a survey, there will be 23% increase in EV demands if electricity comes from renewables (Axsen and Kurani, 2013). It is reasonable to hypothesize that the more electric power generations from renewables, the more demands on EVs. 2. The EV usage costs may be further reduced if battery's charging and discharging characteristics match with electricity cost structures. With economic incentives, EV owners may be motivated to charge batteries during off-peak hours with cheap electricity prices, and "sell" stored electricity to offset peak loads for a power grid. For example, a recent demonstration project in Europe encourages users to select battery's charging and discharging profiles to reduce EV usage costs (Anon, 2017). Theoretically, if EV batteries can be directly connected to power grids in truly "two way fashions," utilities may use EV batteries as storage devices to overcome intermittent nature of solar/wind, and shave the load peaks to reduce operation costs. Then, they definitely have the willingness and margins to implement time based pricing schemes for EV consumers (Riesz and Elliston, 2016; Stram, 2016; Trabish, 2015; Movellan, 2015; Siegel and Hsu, 2017).

1.2. Socioeconomic factors

Since 2010, the total number of EVs has increased quickly, including both BEVs (battery electric vehicles) and PHEVs (plug-in hybrid electric vehicles) (IEA, 2016). Electrified transportation is being accepted by drivers (Dijk et al., 2013). Socioeconomic factors related to the EV demands can be classified in three categories: 1. vehicles, 2. consumers, and 3. external factors. In the vehicle category, factors include costs for vehicles, batteries and usages (Brownstone et al., 2000; IEA, 2011; Lieven et al., 2011; Batley, et al., 2004). This category is important for studies within an individual country or region. Due to

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http://dx.doi.org/10.1016/j.enpol.2017.07.021
Received 29 May 2017; Received in revised form 5 July 2017; Accepted 9 July 2017

small variations in EV models, brands and performances, such category is not considered in this cross-country study. In the consumer category, factors include family sizes, education levels, incomes and ages. Manski and Sherman believed that the family sizes affect the vehicle selections such as number of seats and trunk sizes for the traditional vehicles (Manski and Sherman, 1980). These differences among fourteen countries are relatively small. Therefore, the family size is not considered here. Some research results indicate that higher education levels would lead to more desires for the EVs (Hidrue et al., 2011; Gallagher and Muehlegger, 2011). However, when sample sizes were small, education levels did not show significant impacts (Sierzchula et al., 2014). Thus, it will be meaningful to reexamine the effects of education levels in a cross-country study. Some microeconomic researchers observed direct correlations between family incomes and EV purchases, while others did not see such connections (Hidrue et al., 2011; Gallagher and Muehlegger, 2011; Sierzchula et al., 2014). Macroscopically, GDP per capita should be retested in this cross-country study. In previous studies, factors such as ages and genders were found to be less important than the economic factors, and will not be considered here (Lane and Potter, 2007; Egbue and Long, 2012). In the external factor category, variables include gasoline prices, number of charging stations, population density, and urbanization. In early publications, impacts of gasoline prices were not entirely clear (Gallagher and Muehlegger, 2011; Sierzchula et al., 2014; Diamond, 2009; Beresteanu and Li, 2011). It will be interesting to study the effects while separating BEVs from PHEVs. The number of charging stations represents available infrastructures, and is considered as an important factor by other researchers (Sierzchula et al., 2014; Egbue and Long, 2012; Tran et al., 2012). High population density may lead to high EV adoption rates (IEA, 2016). This paper considers both population density and urbanization as additional variables. Previous studies considered effects due to policy incentives in a region, but such data are not available for the cross-country study (Langbroek et al., 2016; Green et al., 2014).

To our best knowledge, there is no research in the open literature to empirically study the cross-country EV demands, especially from the view point of the renewables. For the first time, the impact of renewables on EV demands is examined empirically. This cross-country panel data study considers the impacts with six additional socio-economic factors. In the rest of the paper, data and model will be described in Section 2, regression results will be presented in Section 3, and policy suggestions will be given in Section 4.

2. Data and model

In this section, the EV demands across fourteen countries are analyzed, with the time period between 2010 and 2015. Independent variables include the percentage of renewables in electricity and six additional socioeconomic factors. Data collections are described in Subsection 2.1, an econometric model is given in Subsection 2.2, and data stationarity test is discussed in 2.3.

2.1. Data collection

For this cross-country study, fourteen countries are considered, including USA, China, Germany, UK, France, Canada, Sweden, Norway, Italy, Spain, Portugal, Japan, South Korea and New Zealand. The annual EV sales volume from these countries represented > 96% global sales. Based on the available data for these countries such as EV sales and number of charging stations, this study covers time period between 2010 and 2015 (Data were from IEA).

For each country, its annual EV sales volume includes both BEVs and PHEVs. The EV-DENSITY is the total annual sales volume per 100 thousand people. Seven independent variables are identified in Table 1: renewables, gas price, charger-density, population-density, GDP per Capita and urbanization, along with source descriptions.

2.2. Model

The dependent variable is the EV-Density, and the independent variables are: 1. Renewables (% of renewable power in total electric power generation); 2. Gas Price (US dollars per liter); 3. Charger-Density; 4. Education; 5. Population-Density; 6. GDP per Capita; and 7. Urbanization. An econometric model for the EV-DENSITY$_{it}$, is established as follows:

$$\begin{aligned}\log(\text{EV}-\text{DENSITY}_{it}) = {} & \beta_1(\text{RENEWABLES}_{it}) + \beta_2\log(\text{GASPRICE}_{it}) \\ & + \beta_3\log(\text{CHARGER}-\text{DENSITY}_{it}) \\ & + \beta_4(\text{EDUCATION}_{it}) + \beta_5\log(\text{POPULATION}-\text{DENSIDY}_{it}) \\ & + \beta_6\log(\text{PERGDP}_{it}) + \beta_7(\text{URBANIZATION}_{it}) \\ & + \gamma_i + \mu_t + \varepsilon_{it} \qquad (1)\end{aligned}$$

where subscripts i and t represents i-th country and *t*-th year, respectively (Sierzchula et al., 2014).

For each variable, there is a regression β coefficient to be determined. The fixed effect for a country is γ_i, and that for a particular year is μ_t. The random disturbance term is ε_{it}. To reduce the level of heteroscedasticity, four variables are taken natural logarithm, along with the EV-Density.

In Table 2, statistical variations for each variable are tabulated. For the EV-Density, the average is 30.32, with the maximum value being 685.35 (Norway, 2015) and the minimum being 0.07 (South Korea, 2010). For the percentage of renewables in total electric power generations, the average is 32.94%, with the maximum (98.10%, Norway, 2015) and the minimum (1.80%, South Korea, 2010). For the gas prices, the average is \$1.73 per liter, with the maximum (\$2.54, Norway, 2013) and the minimum (\$0.62, USA, 2015). For the charger-density, the average is 12.90, with the maximum (135.78, New Zealand, 2015) and the minimum (0.01, Portugal, 2010). For the college educated adults, the average is 34.08%, with the maximum (55.17%, Canada, 2015) and the minimum (9.68%, China, 2010). For the population-density, the average is 186.53, with the maximum (519.30, Japan, 2015) and minimum (3.70, Canada, 2010). For the GDP per capita, the average is \$39,051.99, with the maximum (\$66,817.20, New Zealand, 2013) and the minimum (\$9238.80, China, 2010). For the urbanization, the average is 77.77%, with the maximum (93.50%, Italy, 2015) and minimum (49.20%, China, 2010).

In Table 3, correlation coefficients are provided. Between a pair of independent variables, the largest cross-correlation coefficient is 0.83. Thus, there should be no severe linear correlations during regressions.

2.3. Data stationarity test

The data stationarity test is performed for each variable using a residual-based Lagrange multiplier method (Hadri, 2000). Specifically, this method removes cross-interdependences by means of reducing internal averages within a given group, while allowing some existences for heteroscedasticity. In this test, the null hypothesis assumes that each time series possesses stationarity across interval, and the alternative hypothesis assumes that a unit root exists in the panel data. During the test for each variable, the model includes time evolution tendency and reduces averages in a group, while using heteroscedasticity standard deviations. Testing results are tabulated in Table 4. Each variable testing could not reject null hypothesis. Thus, the data sets are stationary.

3. Regression results

3.1. Results of basic model

There are usually three types of modeling for panel data regressive analyses: fixed effect, random effect and mixed effect. After F-value test and Hausman test, the fixed effect modeling is selected for this study (Hausman, 1978). In Table 5, regression coefficients are tabulated based on four models, in which four, five, six and seven independent