The Impact of Industrial Policies in the New-Energy Vehicle Industry in China

Jingyan Jiang

Information Systems Management Program, Heinz College,

Carnegie Mellon University

Abstract

The new energy vehicles (NEV) in this research refers to battery electric vehicles (BEV) and plug-in hybrid electric vehicles (PHEV). While there are some existing papers about the NEV policies in China, they are mainly focused on qualitative analysis. For the papers that apply quantitative analysis, there are conflicts in their results, and the dataset is quite small. This paper examines the impact of NEV industry policies on new registrations (i.e. sales) of NEV in each province within the same month, using a high-dimensional fixed-effect model. In order to better measure the industrial policies, this study collected over 200 industrial policy documents of each province from government websites and categorized them into seven groups according to the contents. This dataset consists of monthly data from 30 provinces in China from 2013 to 2015. Based on the seven groups of policies, I created six variables: provincial plan, pilot city, promotion policy for charging facilities, charging price concessions, convenient access, and monetary subsidies. This study found that the provincial plan can increase the per capita registrations of BEV by about 34.3 percent. There are also positive effects of the pilot city and convenient access on the BEV registrations. Despite this, these industrial policies have no significant effect on the purchase of PHEV. The reason might be that PHEV also relies mainly on gasoline energy, which is similar to traditional gasoline-energy vehicles. Further, the policy effects are different between private purchase and government procurement.

Key Words: New-Energy Vehicle; Industrial Policies; Policy Effects

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Chapter 1 Introduction

As climate change worsens, the greenhouse effect and energy shortages will become crucial issues. In an attempt to adjust energy structures and reduce pollution from fuel consumption, many countries around the world are promoting the development and adoption of new energy vehicles.

In this process, there are several positive externalities, which exist when a benefit spills over to the society. From the consumption perspective, the adoption of new-energy vehicles will save fossil energy and also reduce the emission of greenhouse gases. This would contribute to the improvement of the sustainable development of the ecological environment, which increases the social benefits and thus generates positive consumption externalities. On the other hand, from the production side, there will be a techniques spillover effect in the research and development of related techniques for new-energy vehicle production, such as the production of electric car batteries. This is another source of positive externalities, production externalities. As we know from the microeconomics model, the social marginal benefits are larger than the private marginal benefits when there exist positive externalities. That will lead to market failure as the market equilibrium cannot reach the socially optimal equilibrium. In this case, it's necessary for governments to provide subsidies in order to achieve the socially optimal outcome (Varian, 2014). Intuitively, the necessity of preferential policies to promote the new-energy vehicles industry is also easy to understand as the manufacturing cost (purchasing cost) and the use cost of the new-energy vehicles are much higher than the competing fossil fuel vehicles. The companies need a large number of funds and other forms of policy support to innovate and reduce the manufacturing cost at the beginning.

In this case, the Chinese government from central to local has released hundreds of relevant preferential policies since 2009 to boost the new-energy vehicle industry. From 2009-2015, the funds for the promotion and adoption of new-energy vehicles from the central government alone reached 33.435 billion yuan (Liu, 2017). With strong policy support, the sales volume of new-energy vehicles experienced explosive growth from 2014 to 2015. The growth rates of sales volume in 2014 and 2015 were 323.78 percent and 342.86 percent respectively. It seems that preferential policies have achieved great success.

However, there are concerns over potential corruption and biases in the implementation process for these policies. Liu (2017) revealed that the sales volume is two times greater than registrations. The number of sales is larger than the number of registrations by 70000. It is estimated that the amount of subsidy fraud was around 1 billion yuan. That is undoubtedly a huge waste of government expenditure. One of the typical subsidy frauds is the reuse of the power battery. In other words, the power battery of the subsidized electric vehicle will be disassembled and reassembled to apply for the production subsidy again. What’s more, excessive subsidies might lead to overcapacity of low-end products, which is also a waste of resources. Because companies might expand blindly with high enthusiasm in order to obtain the subsidies as their first priority is to maximize their profits, regardless of the demand in the market.

Therefore, considering the number of policies, the money invested and the evidence of subsidy fraud, it is vital to evaluate the effectiveness of these preferential policies. In this paper, I focus on studying the Battery Electric Vehicles (BEV) and Plug-in Hybrid Electric Vehicles (PHEV), as they are the two main types of NEV in the market.

Chapter 2 Literature Review

First, we need to have a basic understanding of the development of these industrial policies. Han, et al. (2014) sorted the policies into two phases. Phase 1 is from 2009-2012. During the start of this phase, the subsidy was only available to public procurement, specifically, transit buses and taxis. In 2010, the subsidy was extended to include the private purchase. Between phase 1 and phase 2, there are eight months of policy absence from Jan. 2013 to Aug. 2013. After that in phase 2 (2013-2015), the new electric vehicle subsidy plan was announced in September of 2013 and continued through 2015. It covers both public and private purchases. Later, on Jan. 16, 2016, the Economic Observation Newspaper published an investigation report, The Vanishing New-Energy Vehicles and the Huge Cheated Industry Chain, exposing the hidden rules of subsidy fraud in new-energy vehicles. Noticing this phenomenon, the Ministry of Industry and Information Technology, Development and Reform Commission, Ministry of Finance, and Ministry of Science and Technology jointly launched the fraud investigation. On September 8, 2016, the Ministry of Finance announced the investigation results and circulated a notice of criticism on five typical fraud cases for five different companies, which involved an amount of one billion yuan. In this case, the government started to adjust the preferential policies in the new-energy vehicles industry in 2016.

There is plenty of existing research that focuses on the qualitative analysis of policy evaluation in the new-energy vehicles industry. Liu (2017) pointed out that the demand elasticity of new-energy vehicles is relatively low due to the lack of a complete system for supporting facilities of new energy vehicles. Under this condition, the effect of purchasing subsidies is limited compared to the case with high demand elasticity. In terms of the factors that affect consumer behavior, price, income, and personal preference are the three basic categories. Price includes the price of new-energy vehicles and the price of traditional fossil fuel vehicles. Personal preference is affected by the density of charging infrastructure, the safety of the vehicles, and whether or not the city compiles the Fossil-Fuel-Vehicles Purchase Restriction. This restriction requires people to get a license plate number before purchasing, which is really hard to obtain.

To further investigate the consumer’s evaluation of national new-energy vehicle policies in China, some studies conducted consumer surveys and analyzed the questionnaire data. Li, et al. (2016) analyzed the consumer’s attitudes toward each policy.

They highlighted that macro policies are considered to be of high satisfaction and high importance for people to make decisions, while industry management policies are considered to be of low importance and low satisfaction. The preferential tax and demonstration policies are relatively unimportant, while consumers are satisfied with them.

In contrast, subsidization, technical support, and infrastructure policies were of high importance and low satisfaction. This result provides a good reference when considering the organization or construction of independent variables. Other than the policy factors, the independent variables that affect consumers' adoption intention as well as their environmental concern are also considered, which can serve as the control variable. Wang, et al. (2017) surveyed 324 respondents and concluded that three catalogs of policy measures are positively and significantly related to electric vehicles adoption intention. The convenience policy measures are the most important policy measures, followed by the consumers' environmental concerns. The least important measure is financial incentive policy measures.

As for a quantitative evaluation, few studies have explored the empirical relationships between the implementation and the effects of new-energy vehicle industrial policies in China

I have found three related studies which have conflicting results. Starting from the comparison between subsidy and tax reduction, although the effect of these two instruments seems to be the same theoretically, they are actually very different in practice. In reality, subsidies tend to generate higher transaction costs than tax reduction. Zhou, et al. (2019) found evidence to support this assumption by studying the effects of subsidy and tax reduction on the innovation of new-energy vehicles companies. In this case, we cannot simply add the amount of subsidy and tax reduction together when constructing the policy measurements (the independent variables). They should be regarded as two different factors.

Besides innovation, there are other measurements to evaluate the policy effect. Ma, et al. (2017) found that there is a positive relationship between the market share of new-energy vehicles and the industrial policies, including purchase subsidies, tax deductions, as well as the cancellation of traffic restrictions for new-energy vehicles. However, they also pointed out that the impact of technological progress on the proliferation of new-energy vehicles is larger than the impact of financial subsidies. But the subsidy variable in their study only refers to the upper bound of financial subsidies for new-energy vehicles, regardless of the variation of subsidy level in terms of different types of vehicles. They only considered the four policies mentioned above, which might suffer from omitted variable bias. Also, the generalization ability of their study is still needed to be discussed, as they are based on the data from only six cities from 2011-2016.

Sales volume can also measure the policy effect, as it is the targeting result of the policy. Wang, et al. (2017) used a stepwise linear regression model to analyze the relationship between sales volume and incentives, using the data of 41 pilot cities from 2013 to 2014. They found that the four most important factors affecting sales volume are the density of charging stations, reduced license fees, no driving restrictions, and priority of available land for charging facilities, while the financial subsidies are proved to be insignificant. Considering the eight months subsidy absence, the financial incentives were not in effect for 1/3 of the study period. Therefore, whether subsidy plays a significant role in promoting new- energy vehicles sales should be further explored.

In addition to the policies discussed above, there are two instruments that should be taken into consideration, which are the New-Energy Vehicle Credit Program and Corporate Average Fuel Consumption Regulations for passenger cars. They were finalized in Sep. 2017 and entered implementation on Apr. 1, 2018. According to these regulations, enterprises that fail to reduce production emission and improve the production of new energy vehicles will face heavy financial burdens due to the credit-purchasing or fines, which could force them out of the market. By using a developed game theory-based analysis model, Li, et al. (2018) obtained that these two policies can effectively promote the development of new energy vehicles. With this policy, the proportion of new-energy vehicles in the whole auto market will be up to 3.9 percent. Furthermore, compared with financial subsidies, these two policies can significantly increase the number of new energy vehicles to two times as much as that of the current subsidy level. More importantly, when these two policies are implemented, the financial subsidies will not further promote the development of new energy vehicles.

In sum, the research findings in China’s context are still not clear to present, especially for the effect of financial subsidies. Some studies support that financial subsidies are necessary, while others show that they are inefficient and wasting resources. This may be due to the omitted variable bias, the limitation of data size, the biased measurement of policy effect (e.g., sales volume, which is pointed out to be unreliable as it diverts too much from the registrations).

The model selection might also help to improve the accuracy of the analysis. Wee, et al. (2018) applied a high-dimensional fixed effect regression model, which enables them to control the unobserved heterogeneity by combining two high-dimensional fixed effects, model-province fixed effect and model-time fixed effect. Fitting this model on the data from the 50 U.S. states, they found that if the value of the policy for a state's model-specific electric vehicle increased by $1000, the number of model registrations will increase 5%-11% in the state. This can provide a good reference for my study in China's context.

Chapter 3 Data

To create the database, data are collected from different sources. Data for the independent variable, new-energy vehicle registration, come from the Department of Motor Vehicles. The data of the first two control variables, including population data and per capita income data of each province, are downloaded from the database of the National Bureau of Statistics of China. The data of the other two control variables, gasoline price data and electricity price data in each province, comefrom the WIND database. Most importantly, the dependent variable that represents the industrial policies is collected and sorted from the policy files from the provincial government websites.

The observation unit is the specific model registered in a certain province within the same month. The database is constructed as monthly data from 30 provinces in China (Beijing, Tianjin, Shanghai, Chongqing, Hebei, Shanxi, Liaoning, Jilin, Heilongjiang, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangdong, Hainan, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Inner Mongolia, Guangxi, Ningxia, Xinjiang) from 2013-2015. Taiwan, Hong Kong, Macao, and Tibet are excluded because the registration data are not available.

As for the policy dataset, there is no official dataset recording preferential policies in the new-energy vehicle industry for all provinces in China. In this case, I constructed it manually. Since the policies issued by the central government might also contain specific plans for provinces, I scraped all the related policies issued on the websites of both central government and provincial governments and recorded the effective periods for each of them.

By reading over 200 policy files collected one by one, I identified and grouped all the policies into seven categories: provincial plan, pilot city, promotion policy for charging facilities, charging price concessions, convenient access, vehicle purchase incentives, and reduced vehicle license tax.

- **Provincial plan** represents whether the government's development plan includes promoting the new-energy vehicle industry or not.
- **Pilot city** refers to whether the main cities in the province are selected to be pilot cities in the national development plan for the new-energy vehicle industry.
- **Promotion policy** means that the provincial governments will provide subsidies

or land using priority to promote the construction of the charging facilities.

- **Charging price concessions** are the time-of-use electricity rates specifically for new-energy vehicles' charging.
- **Convenient access incentives** include the free use of expressways and parking privileges such as free parking.
- **Vehicle purchase incentives** are specified for different kinds of new-energy vehicles, which include BEV and PHEV.
- **Reduced vehicle license tax** is the tax reduction for consumers when purchasing new-energy vehicles.

Further, in order to transform these records into real data that can be used in quantitative research. I developed six variables to measure all the policies as Table 1 shows below, which are provincial plan, pilot city, promotion policy for charging facilities, charging price concessions, convenient access, and provincial subsidies. The provincial subsidies include vehicle purchase incentives and reduced vehicle license tax.

Table 1 Summary of NEV Policies in Different Provinces in China

Year	Provincial Plan	Pilot City	Charging Price Concessions	Charging Facilities Promotion	Convenient Access	Provincial Subsidies
2013	Anhui, Beijing, Guangdong, Jiangsu, Shandong, Shaanxi, Shanghai, Tianjin	Beijing, Chongqing, Fujian, Guangdong, Hebei, Hunan, Jiangxi, Shanghai, Tianjin, Zhejiang		Shanghai		
2014	Anhui, Beijing, Guangdong, Hainan, Jiangsu, Shandong, Shaanxi, Shanghai, Tianjin	Beijing, Chongqing, Fujian, Guangdong, Guizhou, Hebei, Hunan, Inner Mongolia, Jiangsu, Jiangxi, Shandon, Shanghai, Tianjin, Yunnan, Zhejiang	Chongqing, Fujian, Gansu, Hebei, Jiangsu, Jiangxi, Shandon, Shanxi, Sichuan	Beijing, Fujian, Gansu, Jiangsu, Jiangxi, Shandong, Shanxi, Shanghai, Sichuan, Tianjin	Shandong, Shanxi, Shanghai	Chongqing, Fujian, Hunan, Jiangsu, Shanghai, Tianjin

Source: Government Websites.

Table 1 Continued

Year	Provincial Plan	Pilot City	Charging Price Concessions	Charging Facilities Promotion	Convenient Access	Provincial Subsidies
2015	Anhui, Beijing, Guangdong, Hainan, Jiangsu, Shandong, Shaanxi, Shanghai, Tianjin	Beijing, Chongqing Fujian, Guangdong, Guizhou, Hebei, Hunan, Inner Mongolia, Jiangsu, Jiangxi, Shandon, Shanghai, Tianjin, Yunnan, Zhejiang	Anhui, Beijing, Chongqing, Fujian, Gansu, Hebei, Hubei, Jiangsu, Jiangxi, Shandon, Shanxi, Sichuan	Anhui, Beijing, Chongqing, Fujian, Gansu, Guizhou, Hubei, Jiangsu, Jiangxi, Shandong, Shanxi, Shanghai, Sichuan, Tianjin	Anhui, Guizhou, Hubei, Shandong, Shanxi, Shanghai	Chongqing, Fujian, Guizhou, Hunan, Jiangsu, Shanxi, Shanghai, Tianjin

Source: Government Websites.

Firstly, I assigned a 0-1 value to the first five variables mentioned above (provincial plan, pilot city, promotion policy for charging facilities, charging price concessions, convenient access), representing whether the specific type of the policy is effective in a given province and period. Secondly, I estimated the monetary value of the vehicle purchase incentives and reduced vehicle license tax for each model in a given province and period, by matching it with related policies based on the rules from the policies I collected. To better explain the purchase incentives, I present a summary of the national subsidy scheme for BEV and PHEV respectively between 2013 and 2015 in China in Table 2. As for the province-specific standards, most of them are similar to the national scheme and too tedious to be shown here. Thus, the Subsidies instrument is constructed by adding the estimated money value of the vehicle purchase incentives and reduced vehicle license tax.

Table 2 Subsidy Standard for BEV and PHEV RMB

	Subsidy Standard (2013)	Subsidy Standard (2014)	Subsidy Standard (2015)
PHEV	35000 (R≥50)	31500 (R≥50)	28000 (R≥50)
BEV	35000 (80≤R<150)	315000 (80≤R<150)	28000 (80≤R<150)
	50000 (150≤R<250)	45000 (150≤R<250)	40000 (150≤R<250)
	60000 (R≥250)	54000 (R≥250)	48000 (R≥250)

Source: Government websites.
R denotes battery range (**km**).

Table 3 and Table 4 show definitions and descriptive statistics for the six policy variables as well as all other variables used in the regression analysis. The values of these six policy variables arecalculated according to the provincial provisions. The average new new-energy vehicle registrations for model i in province p at time t is 33, with a standard deviation of 166.67.,The average net subsidy is about 9912RMB, and the standard deviation is 25048RMB. As for the five policies used to build Index, the average number of effective policies in provincial p at time t is 1.5, and the standard deviation is 1.5.

Table 3 Data Description

Variable	Description
Registrations	Total new registrations for model i in the province p at time t
Regp **(1/million)**	Per capita new registrations for model i in the province p at time t
Provplan **(scalar 0-1)**	Whether the provincial plan includes NEV development in the province p at time t
Pilot **(scalar 0-1)**	Whether the main cities in the province p are selected to be pilot cities in the national development plan for the new-energy vehicle industry at time t
Charp **(scalar 0-1)**	Whether there are charging price concessions in the province p at time t
Charf **(scalar 0-1)**	Whether there are charging facilities promotion policies in the province p at time t
Conve **(scalar 0-1)**	Whether there is convenient access for NEV in the province p at time t
Income **(RMB)**	Per capita income in province p at time t
Electricity **(1000RMB/kWh)**	Residential electricity price in the province p at time t
Population **(million)**	Population in the province p at time t
Gasoline **(RMB/liter)**	Gasoline price in the province p at time t
Subsidies **(10000RMB)**	Monetary value of vehicle purchase incentive, reduced vehicle license tax in the province p at time t

Table 4 Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Registrations	8,568	33.52486	166.673	1	3965
Regp **(1/millions)**	8,568	0.0090192	0.0546539	0.0000932	1.634378
Provplan	8,568	0.2565359	0.4367465	0	1
Pilot	8,568	0.5082866	0.4999605	0	1
Charp	8,568	0.2579365	0.4375244	0	1
Charf	8,568	0.3446545	0.4752832	0	1
Conve	8,568	0.1302521	0.3366002	0	1
Income **(RMB)**	8,568	5327.26	3242.057	912.6667	16622.33
Electricity **(1000RMB/kWh)**	8,568	644.6649	98.15535	381.37	777.24
Population **(millions)**	8,568	5161.384	2874.539	308	10724
Gasoline **(RMB/liter)**	8,568	5.890633	2.326884	0	8.913333
Subsidies **(10000RMB)**	8,568	0.9911531	2.504757	0	12.53

Source: Department of Motor Vehicles, National Bureau of Statistics of China, WIND, Government Websites.

Chapter 4 Empirical Analysis

4.1 Empirical Models and Results

My goal is to investigate how six policy instruments (provincial plan, pilot city, promotion policy for charging facilities, charging price concessions, convenient access, and provincial subsidies) affect the new-energy vehicle purchases, which is measured by new new-energy vehicle registrations per capita in a given province in this case. In order to accomplish this, referring to the empirical method applied by Sherilyn Wee, et al. (2018), I designed a high-dimensional fixed effect regression model, which enables me to control the unobserved heterogeneity by combining two high-dimensional fixed effects to compare the new model registration of a province with the national model registration. One of the high-dimensional fixed effects is the model-province fixed effect, which absorbs time-invariant, province-specific preferences for particular BEV or PHEV models. The other is the model-time fixed effect, reflecting changes in the models provided in the market and changes in vehicle prices and quality.

The baseline empirical model includes only the six dependent variables, policy variables:

$$\log Regp_{ipt} = \beta_0 Provplan_{pt} + \beta_1 Pilot_{pt} + \beta_2 Charf_{pt} + \beta_3 Charp_{pt} + \beta_4 Conve_{pt} + \beta_5 Subsidies_{ipt} + \alpha_{ip} + \gamma_{it} + \varepsilon_{ipt}, \qquad (1)$$

where $\boldsymbol{Regp_{ipt}}$ is new registrations per capita of model i in province p at time t; $\boldsymbol{Provplan_{ipt}}$ refers to the binary variable, provincial plan, in province p at time t, which represents whether the provincial development plan includes promoting the new-energy vehicle industry or not; $\boldsymbol{Pilot_{pt}}$ is the binary variable, pilot city, in province p at time t, reflecting whether there are cities in province p that are selected as pilot cities in the national development plan for the new-energy vehicle industry; $\boldsymbol{Subsidies_{ipt}}$ represents the monetary value of vehicle purchase incentive and reduced vehicle license tax for model i in province p at time t; $\boldsymbol{\alpha_{ip}}$ is a model-province fixed effect; $\boldsymbol{\gamma_{it}}$ is a model-time fixed effect; and $\boldsymbol{\varepsilon_{ipt}}$ is the error term which clusters by model and province. This two-way clustering assumes that errors are independent across models in each province, while they may be correlated for the same model in a given province. The coefficients, $\boldsymbol{\beta_0}$, $\boldsymbol{\beta_1}$, $\boldsymbol{\beta_2}$, $\boldsymbol{\beta_3}$, $\boldsymbol{\beta_4}$, and $\boldsymbol{\beta_5}$, measure the overall policy effect on new new-energy vehicle (BEV and PHEV) registrations.

Before specifying the control variables for the empirical model, it's necessary to identify the causal mechanism between dependent variables and independent variables. Intuitively, the policies will affect the cost of purchase and use of the new-energy vehicles, thus influencing the registrations per capita. As the population of a province might affect both the policies and the cost of purchase and use, this variable should be controlled. Because population will affect the fiscal burden of the government given the same policy and the total cost due to the scale effect. Per capita income of a province might also have the same effect because the target consumers of the new-energy vehicles tend to have higher incomes. In this case, the province with higher income levels might consume more new-energy vehicles. Additionally, income level might affect policy design by affecting the fiscal burden and consumption expectation of the governments. Further, the electricity price and the gasoline price are also likely to affect both policies and registrations per capita. Therefore, these four variables should be controlled to avoid endogeneity. Last but not least, the number of charging stations is long considered to be a necessary control variable according to other studies. In fact, when we investigate the causal mechanism, the promotion policy for charging facilities will affect the number of charging stations directly, and it will then influence the use cost of the new-energy vehicles. In this case, if we control the number of charging stations, the causal effect of the promotion policy for charging facilities on the registrations will be blocked. Therefore, we should not control the number of charging stations.

Based on the identification of the causal reasoning, I obtained the improved empirical model, including the control variables of population, income per capita, gasoline prices, and electricity prices:

$$\log Regp_{ipt} = \beta_0 Provplan_{pt} + \beta_1 Pilot_{pt} + \beta_2 Charf_{pt} + \beta_3 Charp_{pt} + \beta_4 Conve_{pt} + \beta_5 Subsidies_{ipt} + C_{pt} + \alpha_{ip} + \gamma_{it} + \varepsilon_{ipt}, \qquad (2)$$

where C_{pt} is the set of the control variables mentioned above in province p at time t.

According to the data construction process, it's obvious that the policies for BEV and PHEV are quite different. Therefore, I divide the dataset into two subsets, BEV and PHEV in the following empirical analysis. The same models are fitted on the whole sample as well as two subsamples.

Table 5 shows the results for the six regressions (columns 1–6). The model explains about 80%-85% of the variation in new-energy vehicle registrations between the provinces in China. On the one hand, the coefficients of the provincial policy are statistically significant in the first four columns, which identifies the positive effect of provincial policy on the BEV purchase. We can see that the implementation of the provincial policy will increase the registrations of BEV per capita by about 34.3%. On the other hand, I also find that the provincial policy has no statistically significant effect on the PHEV purchase from the coefficients in column 5 and column 6. Besides, the coefficient of charging price concessions in column 6 is negatively significant at the 90% level. The other five policy variables are all statistically insignificant. The reason might be that gasoline, rather than electricity, is the main energy of PHEV in the real-world use case, and driving with energy from gasoline also can charge the battery automatically. In this case, the PHEVs can almost be regarded as gasoline-energy vehicles when considering the effect of charging price concessions, which explains the negative sign of the coefficient.

The coefficients of the other four policy variables are also all statistically insignificant, which indicates the effects of the pilot city, charging facilities promotion, convenient access, and provincial subsidies on the per capita registrations of both BEV and PHEV cannot be identified. One of the reasons might be that the policies may not be implemented immediately in the month of release and the registrations may not be affected immediately. This will be addressed by regressions with lag terms in the robustness check part. Besides, the purchase of new-energy vehicles can be divided into government procurement and private purchase, while most of the government procurement behaviors follow the commands from superior governments. Therefore, government procurement may be less affected by the relevant incentive policies. Therefore, it would be necessary to divide the dataset into private and government subsamples, which will also be discussed in the following robustness check part.

Table 5 Regression Results for New Registrations over Index and Subsidies, 2013–2015.

	(1) Whole Sample	(2) Whole Sample	(3) BEV	(4) BEV	(5) PHEV	(6) PHEV
Provplan	0.0990**	0.0850*	0.364***	0.343***	0.00973	-0.00406
	(0.0487)	(0.0486)	(0.109)	(0.113)	(0.0440)	(0.0425)
Pilot	-0.0249	-0.0166	0.271	0.416	-0.0269	-0.00561
	(0.0566)	(0.0644)	(0.358)	(0.349)	(0.0518)	(0.0573)
Charp	-0.0670	-0.0565	-0.0464	0.0322	-0.0890	-0.119*

	(0.0711)	(0.0688)	(0.175)	(0.171)	(0.0726)	(0.0671)
Charf	0.0272	0.00398	-0.0795	-0.0944	0.0690	0.0618
	(0.0746)	(0.0666)	(0.194)	(0.185)	(0.0768)	(0.0635)
Conve	-0.0823	-0.0754	-0.0734	-0.0777	-0.0662	-0.0709
	(0.101)	(0.101)	(0.315)	(0.306)	(0.0786)	(0.0790)
Subsidies	1.52e-06	0.00119	-0.0356	-0.0238	0.00521	0.00826
	(0.0126)	(0.0131)	(0.0760)	(0.0756)	(0.0100)	(0.00975)
Log (Income)		0.253		0.0301		0.295
		(0.356)		(1.016)		(0.317)
Log (Electricity)		2.487*		6.045		2.315*
		(1.295)		(4.981)		(1.256)
Log (Gasoline)		1.293		-2.244		1.417
		(1.328)		(4.705)		(1.051)
Log (Population)		-2.418		5.861		-5.393
		(4.620)		(11.42)		(5.098)
Constant	-6.444***	-6.819	-6.674***	-91.85	-6.306***	18.74
	(0.120)	(37.10)	(0.282)	(81.50)	(0.127)	(41.16)
Observations	7,884	6,885	2,477	2,306	5,407	4,579
R-squared	0.840	0.840	0.783	0.782	0.877	0.879

Robust standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

4.2 Robustness Check

First, I introduced the lag terms from one month to five months into the model and fit them on the BEV and PHEV subsamples, respectively. Table 6 and Table 7 in the appendix show the lag terms regression results of BEV subsample and PHEV subsample. From column 6 in both tables, it is evident that the coefficients of the five-months lag terms are all statistically insignificant, as the p-values are all larger than 0.1. Therefore, I didn't extend the lag terms to six months. The model explains about 80 percent of the variation for the BEV subsample, while it explains about 90 percent of the variation for the PHEV subsample.

As seen in Table 6, the coefficients of the two-months lag terms of provincial policy and convenient access are consistently significant from column 3 to 6. The consistent statistical significance indicates the provincial policy and convenient access incentives released with a two month lead time will increase the per capita registrations of BEV in a given province at certain months by 33.2%-46.8% and 61.1%-90.1%, respectively. There are also other significant coefficients in Table 6, which are not consistent across every regression. In this case, the significance of those coefficients is not reliable. In this case, the effects of the other four policies (pilot city, charging facilities promotion, charging price concessions, and provincial subsidies) on BEV purchase cannot be identified.

Table 7 shows that the coefficients (0.0815, 0.0919, 0.114) of the provincial policy are statistically significant from column 4 to 6 due to the p-value being larger than 0.1. It reveals the positive effect of the provincial policy on PHEV purchases. The effect of the provincial policy will increase the per capita registrations of the PHEV by 8.15 percent to 11.4 percent. In addition, the coefficients of the charging price concessions are negatively significant in the first three columns. The reason might be the same as I mentioned in the analysis of Table 5. However, these coefficients' significance are not reliable due to inconsistency across all 6 columns.

Additionally, I further divided the two subsamples into Private-purchase, Government-procurement, BEVP, BEVG, PHEVP, and PHEVG, where P represents the private purchase and G indicates the government procurement. Tables 8-13 in the appendix below show the regression results of the six subsamples, respectively.

As for the Private-purchase subsample, the model explains about 87 percent of the variation. The coefficients of the four-month lag term of the pilot city in column 5 and 6 of Table 8 are statistically significant. This indicates the effect of being selected as pilot cities four months before will increase the per capita registrations of the new-energy vehicles by 16.4%-26.6%.

Per Table 9, the lag-term model explains about 77 percent of the variation for the Government-procurement subsample, which is lower than the Private-purchase subsample. One possible explanation might be that the observations in Government-procurement are much fewer than Private-purchase subsample. Additionally, the coefficients of the one-month lag term of the provincial policy are positively significant from columns 3 to 6. Intuitively, this difference is reasonable as government procurement is strongly correlated with the government plans because the government tends to use procurement as a positive signal to encourage private purchases. Therefore, if the promotion of the new-energy vehicle industry is included in the governments' development plans, it's likely that they will expand the procurement of new-energy vehicles. In addition, the coefficients of the two-months lag term of charging facilities promotion are negatively significant from column 3 to column 6. It might seem counterintuitive but can be explained by considering the fiscal budget, as both procurement of new-energy vehicles and charging facilities promotion increase the governments' fiscal expenditure in promoting this industry. They can be regarded as competitors as the fiscal budget is limited.

As for the subsamples of BEVP and BEVG, the model explains about 85 percent and 70 percent of the variation, respectively. In Table 10, the coefficients of the three-months lag term of the pilot city are consistently significant from column 4 to column 6. That reveals the effect of being pilot cities three months before present will increase the private per capita registrations of BEV by 66.5%-84.8%. Additionally, the coefficients of the four-months lag term of the provincial policy in columns 5 and 6 are positively significant at the 99 percent level, which identifies the positive effect of provincial policy again. From Table 11, we can observe that there are only three regressions. Since the sample size of BEVG is relatively small with the high-dimensional fixed-effects, adding too many lag terms will cause multicollinearity, which means the independent variables would be highly correlated to each other. In this case, many variables will be omitted. The results are not stable or reliable because the omitted variables are randomly picked when modeling.

Tables 12 and 13 represent the regression results on PHEVP and PHEVG subsamples. As seen below, the significance of the coefficients is not stable in both tables. In this case, there is not sufficient evidence for the causation inference. Contributing factors could include that the PHEVs are similar to the traditional gasoline-energy vehicles in the real-world use case, relying on gasoline as the main energy. The policy incentives focusing on new energy cannot impact the purchase of PHEVs significantly. These results are also consistent with the previous analysis in Table 5.

Chapter 5 Conclusion

This research uses the high-dimensional fixed effect model to evaluate how the industrial policies of the new-energy vehicle industry affect the registration of the new-energy vehicle in each province in China.

First, I discovered that the provincial plan significantly increases the purchase of BEV. A 34.3 percent increase of per capita registrations of BEV in a given province at a certain month would occur if the government includes the promotion of the new-energy vehicles industry in the provincial development plans. This result is also proved to be robust in the robustness check section with lag term regressions and subsample analysis. The results of the robustness check also reveal the lag effects of the provincial plan, pilot city, and convenient access policies.

Second, this research also shows that industrial policies have no significant effect on the purchase of PHEV. As I mentioned previously, this lack of significance could be attributed to the similarity between PHEV and traditional gasoline-energy vehicles. In the real-world use case, PHEV relies mainly on gasoline energy rather than electricity. Therefore, these promotion policies, aiming to develop the electricity application in vehicles, would not be able to impact the purchase of PHEV effectively.

Third, the policy effects are different between private purchase and government procurement. The provincial plans affect government procurement more rapidly and significantly than private purchase, as they correlate with government procurement naturally. Meanwhile, the promotion policies for charging facilities have a negative effect on government procurement. The reason might be that they are in the same fiscal budget pool competing for funds, as procurement of new-energy vehicles and charging facilities promotion would increase the governments' fiscal expenditure. Given that there is a fiscal budget constraint for every category and these two policies are from the same category, they might be competitors to each other in terms of funding.

Last, it is counterintuitive that the money value subsidies have no effect on the new-energy vehicle purchase in this research. It is likely to be the result of data limitation. The dataset of registrations does not contain the battery range data for each model. In this case, I can only match the money value subsidies with models generally by energy type (BEV or PHEV), rather than the specific battery range required in the subsidy standards.

Therefore, it is hard to conclude whether the money value subsidies are effective here. It is necessary to do further research about them when the data is available.

Appendix

Table 6 Regression Results of BEV Subsample with Lag Terms (Lag1-Lag5), 2013–2015.

	(1) BEV	(2) BEV	(3) BEV	(4) BEV	(5) BEV	(6) BEV
Provplan	0.343***	0.247**	0.131	-0.0219	0.0545	-0.0733
	(0.113)	(0.119)	(0.156)	(0.178)	(0.220)	(0.285)
Pilot	0.416	-0.0152	-0.182	-0.220	-0.401	-0.357
	(0.349)	(0.348)	(0.338)	(0.227)	(0.282)	(0.267)
Charp	0.0322	-0.0397	0.232	0.351	0.364	0.320
	(0.171)	(0.197)	(0.223)	(0.233)	(0.272)	(0.254)
Charf	-0.0944	0.184	-0.219	-0.306	-0.0921	0.137
	(0.185)	(0.265)	(0.302)	(0.294)	(0.345)	(0.351)
Conve	-0.0777	-0.437	-0.00696	0.0154	-0.164	-0.415
	(0.306)	(0.342)	(0.367)	(0.389)	(0.434)	(0.389)
Subsidies	-0.0238	-0.0160	-0.0377	-0.00432	0.103	0.112
	(0.0756)	(0.0937)	(0.115)	(0.135)	(0.167)	(0.135)
Lag_Provplan1		0.324**	0.268*	0.209	0.117	-0.00347
		(0.128)	(0.143)	(0.158)	(0.162)	(0.196)
Lag_Pilot1		0.826***	0.596	0.209	0.158	0.370
		(0.285)	(0.423)	(0.448)	(0.536)	(0.585)
Lag_Charp1		0.0372	-0.164	-0.276	-0.217	-0.128
		(0.230)	(0.223)	(0.197)	(0.226)	(0.243)
Lag_Charf1		-0.367	0.390	0.427	0.357	0.756**
		(0.274)	(0.247)	(0.302)	(0.324)	(0.382)
Lag_Conve1		0.451	-0.695**	-0.791**	-0.638	-1.078**
		(0.361)	(0.328)	(0.375)	(0.392)	(0.459)
Lag_Subsidies1		-0.0896	-0.0815	-0.0592	-0.0942	-0.0225
		(0.0827)	(0.0870)	(0.117)	(0.138)	(0.151)
Lag_Provplan2			0.347***	0.332**	0.335*	0.468*
			(0.124)	(0.130)	(0.172)	(0.252)
Lag_Pilot2			0.483	0.503	0.0974	-0.727
			(0.321)	(0.578)	(0.534)	(0.671)
Lag_Charp2			0.0444	-0.0830	-0.0177	-0.144
			(0.207)	(0.227)	(0.215)	(0.230)
Lag_Charf2			-0.488*	-0.0718	-0.0378	-0.0276
			(0.281)	(0.285)	(0.300)	(0.253)
Lag_Conve2			0.901***	0.744**	0.611*	0.722*
			(0.339)	(0.360)	(0.350)	(0.369)
Lag_Subsidies2			-0.00305	-0.0957	-0.0970	-0.129
			(0.0709)	(0.0940)	(0.111)	(0.131)
Lag_Provplan3				0.0283	0.0614	0.120
				(0.132)	(0.128)	(0.193)
Lag_Pilot3				0.451	0.257	1.191*
				(0.528)	(0.396)	(0.663)

Table 6 Continued

	(1) BEV	(2) BEV	(3) BEV	(4) BEV	(5) BEV	(6) BEV
Lag_Charp3				0.227	0.127	0.221
				(0.206)	(0.205)	(0.223)
Lag_Charf3				-0.364	-0.178	-0.498*
				(0.269)	(0.282)	(0.298)
Lag_Conve3				0.201	-0.0660	0.351
				(0.382)	(0.394)	(0.413)
Lag_Subsidies3				0.0320	-0.0722	-0.0713
				(0.0803)	(0.0994)	(0.120)
Lag_Provplan4					-0.0950	-0.133
					(0.114)	(0.104)
Lag_Pilot4					1.012**	0.537
					(0.472)	(0.796)
Lag_Charp4					-0.0176	0.0380
					(0.166)	(0.211)
Lag_Charf4					-0.320	-0.310
					(0.195)	(0.242)
Lag_Conve4					0.366	0.0384
					(0.312)	(0.400)
Lag_Subsidies4					0.0168	-0.000284
					(0.0840)	(0.0821)
Lag_Provplan5						-0.109
						(0.133)
Lag_Pilot5						0.283
						(0.500)
Lag_Charp5						-0.170
						(0.196)
Lag_Charf5						0.190
						(0.189)
Lag_Conve5						0.102
						(0.378)
Lag_Subsidies5						-0.116
						(0.0895)
Log (Income)	0.0301	0.136	0.414	0.178	0.677	1.326
	(1.016)	(1.110)	(1.133)	(1.280)	(1.444)	(1.584)
Log (Electricity)	6.045	4.260	6.261	8.277	6.159	5.214
	(4.981)	(5.698)	(6.422)	(7.406)	(8.672)	(9.311)
Log (Gasoline)	-2.244	0.471	0.639	2.087	7.307	8.670
	(4.705)	(5.097)	(5.997)	(5.933)	(6.318)	(6.909)
Log (Population)	5.861	9.755	13.74	17.61	11.62	2.372
	(11.42)	(12.78)	(16.88)	(19.36)	(22.06)	(21.04)

Table 6 Continued

	(1) BEV	(2) BEV	(3) BEV	(4) BEV	(5) BEV	(6) BEV
Constant	-91.85	-119.4	-169.1	-215.8	-165.5	-88.92
	(81.50)	(89.77)	(124.6)	(145.9)	(163.6)	(155.1)
Observations	2,306	1,981	1,722	1,498	1,299	1,131
R-squared	0.782	0.792	0.797	0.809	0.825	0.837

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7 Regression Results of PHEV Subsample with Lag Terms (Lag1-Lag5), 2013–2015.

	(1) PHEV	(2) PHEV	(3) PHEV	(4) PHEV	(5) PHEV	(6) PHEV
Provplan	-0.00406	0.0171	0.0567	0.0815*	0.0919*	0.114**
	(0.0425)	(0.0466)	(0.0478)	(0.0484)	(0.0486)	(0.0483)
Pilot	-0.00561	0.0657	0.0670	0.0489	0.0120	-0.0295
	(0.0573)	(0.0848)	(0.0897)	(0.102)	(0.111)	(0.119)
Charp	-0.119*	-0.181*	-0.194*	-0.148	-0.148	-0.152
	(0.0671)	(0.100)	(0.104)	(0.103)	(0.102)	(0.101)
Charf	0.0618	0.0141	0.0309	-0.00860	0.0280	0.0520
	(0.0635)	(0.0887)	(0.0922)	(0.0935)	(0.0949)	(0.0934)
Conve	-0.0709	0.0776	0.0501	0.0995	0.0446	0.0240
	(0.0790)	(0.139)	(0.140)	(0.144)	(0.143)	(0.141)
Subsidies	0.00826	-0.0128	0.00718	0.00958	0.0113	0.0106
	(0.00975)	(0.0195)	(0.0165)	(0.0164)	(0.0168)	(0.0172)
Lag_Provplan1		-0.0635	-0.0674	-0.0696	-0.0647	-0.0625
		(0.0522)	(0.0548)	(0.0613)	(0.0706)	(0.0795)
Lag_Pilot1		-0.0604	0.0140	-0.0329	-0.0409	-0.0292
		(0.0943)	(0.109)	(0.121)	(0.130)	(0.137)
Lag_Charp1		0.110	-0.0105	-0.0785	-0.0160	-0.0445
		(0.103)	(0.105)	(0.122)	(0.115)	(0.112)
Lag_Charf1		0.0365	0.0320	0.110	0.0281	0.00689
		(0.0905)	(0.108)	(0.118)	(0.128)	(0.133)
Lag_Conve1		-0.184	-0.183	-0.296	-0.217	-0.143
		(0.152)	(0.162)	(0.182)	(0.180)	(0.189)
Lag_Subsidies1		0.0259	-0.00167	0.00364	0.00600	0.00631
		(0.0214)	(0.0245)	(0.0275)	(0.0278)	(0.0289)
Lag_Provplan2			-0.0677	-0.0668	-0.0735	-0.0935**
			(0.0446)	(0.0465)	(0.0475)	(0.0444)
Lag_Pilot2			-0.0661	0.0415	0.0791	0.0766
			(0.0765)	(0.106)	(0.111)	(0.120)
Lag_Charp2			0.177	0.157	0.106	0.154
			(0.124)	(0.133)	(0.126)	(0.127)

Table 7 Continued

	(1) PHEV	(2) PHEV	(3) PHEV	(4) PHEV	(5) PHEV	(6) PHEV
Lag_Charf2			-0.0424	-0.0764	-0.00884	0.0326
			(0.100)	(0.112)	(0.119)	(0.133)
Lag_Conve2			0.0427	0.233	0.151	0.136
			(0.145)	(0.194)	(0.207)	(0.207)
Lag_Subsidies2			0.00810	-0.0136	-0.0261	-0.0336
			(0.0213)	(0.0256)	(0.0255)	(0.0256)
Lag_Provplan3				-0.0306	-0.0691	-0.0537
				(0.0464)	(0.0559)	(0.0582)
Lag_Pilot3				-0.0466	-0.0757	-0.134
				(0.114)	(0.144)	(0.154)
Lag_Charp3				0.0596	0.0752	0.0747
				(0.0764)	(0.0985)	(0.102)
Lag_Charf3				-0.0435	-0.0104	-0.0925
				(0.0768)	(0.116)	(0.124)
Lag_Conve3				-0.160	-0.265	-0.276
				(0.173)	(0.183)	(0.198)
Lag_Subsidies3				0.0197	-0.00254	-0.000207
				(0.0187)	(0.0236)	(0.0258)
Lag_Provplan4					0.0459	0.0604
					(0.0431)	(0.0500)
Lag_Pilot4					0.0426	0.107
					(0.0902)	(0.113)
Lag_Charp4					-0.00896	-0.0377
					(0.0963)	(0.0803)
Lag_Charf4					-0.103	0.0526
					(0.109)	(0.0934)
Lag_Conve4					0.181	0.0549
					(0.136)	(0.137)
Lag_Subsidies4					0.0334*	0.0191
					(0.0200)	(0.0217)
Lag_Provplan5						-0.0241
						(0.0605)
Lag_Pilot5						0.0102
						(0.0842)
Lag_Charp5						-0.0117
						(0.106)
Lag_Charf5						-0.125
						(0.112)
Lag_Conve5						0.0957
						(0.138)

Table 7 Continued

	(1) PHEV	(2) PHEV	(3) PHEV	(4) PHEV	(5) PHEV	(6) PHEV
Lag_Subsidies5						0.0205
						(0.0189)
Log (Income)	0.295	0.368	0.589	0.685*	0.729*	0.719*
	(0.317)	(0.345)	(0.363)	(0.386)	(0.391)	(0.418)
Log (Electricity)	2.315*	2.281*	2.060	2.118	2.360*	2.626**
	(1.256)	(1.224)	(1.316)	(1.310)	(1.264)	(1.260)
Log (Gasoline)	1.417	1.092	1.477	1.536	1.268	1.500
	(1.051)	(1.035)	(1.128)	(1.231)	(1.275)	(1.344)
Log (Population)	-5.393	-4.186	-3.444	-2.286	-2.343	-2.364
	(5.098)	(5.019)	(5.074)	(5.283)	(5.253)	(5.406)
Constant	18.74	8.928	1.612	-9.312	-10.21	-12.02
	(41.16)	(40.46)	(40.71)	(43.04)	(42.96)	(44.64)
Observations	4,579	4,099	3,733	3,396	3,157	2,945
R-squared	0.879	0.879	0.883	0.881	0.882	0.881

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 8 Regression Results of Private Subsample with Lag Terms (Lag1-Lag5), 2013-2015.

	(1) Private	(2) Private	(3) Private	(4) Private	(5) Private	(6) Private
Provplan	-0.0896	-0.0767	-0.0248	-0.0106	0.0141	0.00367
	(0.0617)	(0.0851)	(0.0728)	(0.0743)	(0.0821)	(0.0972)
Pilot	-0.0738	-0.116	-0.0667	-0.116	-0.110	-0.103
	(0.0593)	(0.0838)	(0.0820)	(0.0878)	(0.0935)	(0.0997)
Charp	0.0174	-0.123	-0.0624	0.0338	0.00793	0.00217
	(0.0622)	(0.0922)	(0.0964)	(0.0990)	(0.0980)	(0.0965)
Charf	-0.0392	0.00709	-0.0321	-0.0636	0.000228	0.0290
	(0.0627)	(0.0981)	(0.103)	(0.107)	(0.103)	(0.103)
Conve	-0.0684	0.0358	0.0818	0.0540	-0.0229	-0.00940
	(0.101)	(0.133)	(0.134)	(0.145)	(0.150)	(0.147)
Subsidies	0.00403	-0.0138	0.00112	0.0194	0.0262	0.0283
	(0.0139)	(0.0199)	(0.0182)	(0.0197)	(0.0212)	(0.0218)
Lag_Provplan1		-0.00522	-0.0626	-0.0592	-0.0900	-0.100
		(0.0809)	(0.0809)	(0.0914)	(0.0976)	(0.108)
Lag_Pilot1		0.109	0.0490	0.0437	0.0483	0.0395
		(0.0985)	(0.118)	(0.120)	(0.129)	(0.131)
Lag_Charp1		0.158	-0.0313	-0.135	-0.0854	-0.0640
		(0.103)	(0.103)	(0.115)	(0.111)	(0.108)
Lag_Charf1		-0.0611	0.00735	0.0434	-0.00640	-0.0181
		(0.100)	(0.0991)	(0.112)	(0.116)	(0.112)
Lag_Conve1		-0.132	-0.200	-0.175	-0.119	-0.128
		(0.160)	(0.171)	(0.167)	(0.176)	(0.180)
Lag_Subsidies1		0.0184	-0.00437	-0.00330	0.00325	0.00331
		(0.0211)	(0.0254)	(0.0292)	(0.0325)	(0.0331)

Table 8 Continued

	(1) Private	(2) Private	(3) Private	(4) Private	(5) Private	(6) Private
Lag_Provplan2			-0.00900	-0.0584	-0.0397	-0.0689
			(0.0617)	(0.0818)	(0.0833)	(0.0861)
Lag_Pilot2			-0.000340	-0.0890	-0.104	-0.125
			(0.0827)	(0.0937)	(0.0963)	(0.101)
Lag_Charp2			0.176*	0.114	0.0922	0.0514
			(0.0967)	(0.106)	(0.0966)	(0.102)
Lag_Charf2			-0.0629	0.00352	0.0300	0.0615
			(0.102)	(0.110)	(0.110)	(0.109)
Lag_Conve2			0.0363	0.0302	0.109	0.0732
			(0.150)	(0.162)	(0.162)	(0.171)
Lag_Subsidies2			0.00623	-0.0219	-0.0358	-0.0458*
			(0.0238)	(0.0231)	(0.0235)	(0.0245)
Lag_Provplan3				0.0521	0.0526	0.0540
				(0.0934)	(0.118)	(0.113)
Lag_Pilot3				0.135	0.0151	-0.0129
				(0.0978)	(0.115)	(0.117)
Lag_Charp3				0.105	0.0717	0.119
				(0.0828)	(0.0935)	(0.0979)
Lag_Charf3				-0.111	-0.00249	-0.0472
				(0.0772)	(0.0979)	(0.106)
Lag_Conve3				-0.00608	-0.307*	-0.172
				(0.159)	(0.176)	(0.174)
Lag_Subsidies3				0.0125	-0.00646	-0.00393
				(0.0194)	(0.0213)	(0.0232)
Lag_Provplan4					-0.0107	0.107
					(0.0818)	(0.0943)
Lag_Pilot4					0.164*	0.266**
					(0.0886)	(0.108)
Lag_Charp4					-0.0105	0.0162
					(0.0801)	(0.0825)
Lag_Charf4					-0.150	-0.178*
					(0.0969)	(0.0931)
Lag_Conve4					0.274**	0.0945
					(0.136)	(0.144)
Lag_Subsidies4					0.0201	0.0250
					(0.0163)	(0.0219)
Lag_Provplan5						-0.0764
						(0.0810)
Lag_Pilot5						-0.0845
						(0.0866)

Table 8 Continued

	(1) Private	(2) Private	(3) Private	(4) Private	(5) Private	(6) Private
Lag_Charp5						-0.0752
						(0.0908)
Lag_Charf5						0.0725
						(0.0890)
Lag_Conve5						0.0532
						(0.151)
Lag_Subsidies5						0.00398
						(0.0222)
Log (Income)	0.579*	0.658*	0.753**	0.910**	0.891**	1.023**
	(0.324)	(0.350)	(0.358)	(0.379)	(0.393)	(0.435)
Log (Electricity)	3.619***	3.724***	3.532***	3.327**	3.319***	3.073**
	(1.284)	(1.271)	(1.335)	(1.315)	(1.277)	(1.436)
Log (Gasoline)	1.137	1.078	2.011*	2.105*	2.119	1.839
	(1.101)	(1.091)	(1.182)	(1.261)	(1.285)	(1.348)
Log (Population)	1.365	0.380	1.106	1.510	0.674	0.172
	(4.904)	(5.108)	(5.330)	(5.525)	(5.564)	(5.945)
Constant	-48.47	-41.29	-48.67	-52.16	-44.98	-39.69
	(41.23)	(43.16)	(45.21)	(47.39)	(48.14)	(51.66)
Observations	5,996	5,349	4,805	4,340	3,978	3,658
R-squared	0.861	0.870	0.878	0.878	0.880	0.883

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 9 Regression Results of Government Subsample with Lag Terms (Lag1-Lag5), 2013-2015.

	(1)	(2)	(3)	(4)	(5)	(6)
	Gov	**Gov**	**Gov**	**Gov**	**Gov**	**Gov**
Provplan	0.0144	-0.0216	-0.157	-0.212	-0.240	-0.180
	(0.0732)	(0.0964)	(0.127)	(0.144)	(0.156)	(0.147)
Pilot	0.0761	-0.0455	-0.123	-0.0736	-0.107	-0.248
	(0.0751)	(0.0990)	(0.115)	(0.127)	(0.140)	(0.181)
Charp	-0.0232	0.192	0.176	0.188	0.206	0.121
	(0.161)	(0.167)	(0.193)	(0.202)	(0.206)	(0.231)
Charf	0.0654	0.0971	0.0334	0.0344	-0.0769	-0.0723
	(0.112)	(0.142)	(0.162)	(0.177)	(0.197)	(0.209)
Conve	-0.135	-0.345*	-0.259	-0.276	-0.269	-0.183
	(0.154)	(0.187)	(0.213)	(0.230)	(0.270)	(0.307)
Subsidies	0.00772	0.00977	0.0176	0.00683	0.0308	0.00244
	(0.0161)	(0.0238)	(0.0290)	(0.0321)	(0.0338)	(0.0371)
Lag_Provplan1		0.0188	0.283*	0.344*	0.396*	0.691***
		(0.101)	(0.164)	(0.196)	(0.235)	(0.251)
Lag_Pilot1		0.0701	0.213	0.0959	0.0902	0.102
		(0.122)	(0.130)	(0.146)	(0.156)	(0.184)
Lag_Charp1		-0.206	-0.235	-0.248	-0.321	-0.220
		(0.204)	(0.206)	(0.222)	(0.234)	(0.248)
Lag_Charf1		-0.0351	0.282*	0.258	0.398*	0.297
		(0.135)	(0.151)	(0.192)	(0.207)	(0.197)
Lag_Conve1		0.272	-0.0848	-0.173	-0.156	-0.250
		(0.267)	(0.274)	(0.289)	(0.337)	(0.350)
Lag_Subsidies1		-0.00475	-0.00500	0.0191	-0.00830	0.0220
		(0.0292)	(0.0347)	(0.0386)	(0.0465)	(0.0456)
Lag_Provplan2			-0.166	-0.278	-0.208	-0.332
			(0.160)	(0.237)	(0.245)	(0.296)
Lag_Pilot2			-0.116	-0.0109	-0.131	-0.0607
			(0.151)	(0.169)	(0.157)	(0.184)
Lag_Charp2			0.0860	0.314	0.332	0.229
			(0.182)	(0.220)	(0.262)	(0.293)
Lag_Charf2			-0.319*	-0.470**	-0.512**	-0.434*
			(0.164)	(0.191)	(0.224)	(0.238)
Lag_Conve2			0.317	0.359	0.320	0.332
			(0.255)	(0.335)	(0.380)	(0.389)
Lag_Subsidies2			-0.00714	-0.0264	-0.0114	-0.0146
			(0.0345)	(0.0426)	(0.0483)	(0.0474)

Table 9 Continued

	(1) Gov	(2) Gov	(3) Gov	(4) Gov	(5) Gov	(6) Gov
Lag_Provplan3				0.00937	-0.00424	-0.138
				(0.121)	(0.177)	(0.230)
Lag_Pilot3				-0.0369	0.141	0.0906
				(0.164)	(0.179)	(0.172)
Lag_Charp3				-0.325**	-0.257	-0.176
				(0.153)	(0.175)	(0.183)
Lag_Charf3				0.303*	0.237	0.256
				(0.156)	(0.186)	(0.230)
Lag_Conve3				-0.0196	-0.134	0.256
				(0.302)	(0.323)	(0.336)
Lag_Subsidies3				0.0260	0.0249	0.00499
				(0.0368)	(0.0380)	(0.0366)
Lag_Provplan4					-0.0361	-0.210
					(0.123)	(0.208)
Lag_Pilot4					-0.0505	0.0554
					(0.190)	(0.149)
Lag_Charp4					0.0546	0.133
					(0.174)	(0.210)
Lag_Charf4					-0.0430	0.000167
					(0.153)	(0.179)
Lag_Conve4					0.197	-0.180
					(0.380)	(0.433)
Lag_Subsidies4					-0.0105	0.0478
					(0.0436)	(0.0459)
Lag_Provplan5						0.0861
						(0.134)
Lag_Pilot5						0.0896
						(0.132)
Lag_Charp5						-0.284
						(0.253)
Lag_Charf5						0.168
						(0.139)
Lag_Conve5						0.0866
						(0.361)
Lag_Subsidies5						-0.0595
						(0.0404)
Log (Income)	0.0891	0.302	0.661	0.499	0.759	0.964
	(0.697)	(0.813)	(0.851)	(0.948)	(0.988)	(1.059)
Log (Electricity)	2.166	3.884	4.948	6.176	5.352	6.194
	(2.167)	(2.974)	(3.396)	(3.796)	(3.779)	(4.101)

Table 9 Continued

	(1) Gov	(2) Gov	(3) Gov	(4) Gov	(5) Gov	(6) Gov
Log (Gasoline)	-2.472	-0.439	1.551	2.273	2.955	1.411
	(2.700)	(3.006)	(3.491)	(3.475)	(3.730)	(3.944)
Log (Population)	-10.000*	-8.227	-7.052	-9.676	-10.08	-11.71
	(5.933)	(7.311)	(9.143)	(10.09)	(12.38)	(14.40)
Constant	67.21	35.43	11.83	26.21	31.76	41.20
	(48.06)	(57.92)	(71.83)	(79.06)	(100.1)	(116.6)
Observations	3,525	2,977	2,525	2,137	1,855	1,618
R-squared	0.759	0.767	0.769	0.777	0.791	0.805

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 10 Regression Results of BEVP Subsample with Lag Terms (Lag1-Lag5), 2013-2015.

	(1) BEVP	(2) BEVP	(3) BEVP	(4) BEVP	(5) BEVP	(6) BEVP
Provplan	1.241***	0.0865	0.636	0.645	0.875	0.884
	(0.324)	(0.426)	(0.560)	(0.584)	(0.694)	(0.970)
Pilot	0.189	-0.0232	-0.149	-0.366	-0.428	-0.294
	(0.300)	(0.313)	(0.238)	(0.426)	(0.346)	(0.357)
Charp	0.208	-0.0438	0.119	0.345	0.397*	0.461
	(0.157)	(0.182)	(0.185)	(0.218)	(0.224)	(0.278)

Table 10 Continued

	(1)	(2)	(3)	(4)	(5)	(6)
	BEVP	**BEVP**	**BEVP**	**BEVP**	**BEVP**	**BEVP**
Charf	-0.196	-0.0179	-0.254	-0.136	0.0277	-0.0309
	(0.208)	(0.282)	(0.298)	(0.392)	(0.437)	(0.451)
Conve	-0.106	-0.161	0.0174	-0.276	-0.520	-0.493
	(0.334)	(0.294)	(0.334)	(0.407)	(0.497)	(0.485)
Subsidies	0.00858	-0.0182	0.0151	0.0548	0.0936	0.132
	(0.0714)	(0.0810)	(0.100)	(0.131)	(0.141)	(0.129)
Lag_Provplan1		1.125***	-0.0988	0.285	0.706	-0.349
		(0.319)	(0.343)	(0.357)	(0.619)	(0.535)
Lag_Pilot1		0.580*	0.0135	0.239	0.522	0.731
		(0.297)	(0.423)	(0.745)	(0.614)	(0.568)
Lag_Charp1		0.284	-0.0185	-0.148	-0.234	-0.0992
		(0.196)	(0.202)	(0.202)	(0.216)	(0.241)
Lag_Charf1		-0.231	0.159	-0.0631	0.438	0.751*
		(0.301)	(0.271)	(0.406)	(0.394)	(0.414)
Lag_Conve1		0.0377	-0.354	-0.0289	-0.440	-0.909*
		(0.377)	(0.407)	(0.439)	(0.424)	(0.464)
Lag_Subsidies1		-0.0352	-0.0429	-0.00992	0.0279	0.0554
		(0.0891)	(0.102)	(0.127)	(0.151)	(0.180)
Lag_Provplan2			1.145***	-0.607	-0.458	0.490
			(0.180)	(0.389)	(0.330)	(0.359)
Lag_Pilot2			0.506	-0.0852	-0.733*	-1.212***
			(0.360)	(0.634)	(0.397)	(0.457)
Lag_Charp2			0.206	0.0356	0.0599	-0.0592
			(0.175)	(0.179)	(0.193)	(0.209)
Lag_Charf2			-0.212	0.236	-0.131	-0.220
			(0.254)	(0.259)	(0.334)	(0.179)
Lag_Conve2			0.256	-0.0447	0.427	0.559*
			(0.380)	(0.355)	(0.394)	(0.336)
Lag_Subsidies2			-0.00290	-0.0770	-0.0473	-0.0383
			(0.0752)	(0.0804)	(0.0925)	(0.111)
Lag_Provplan3				1.643***	0.0901	0.0107
				(0.298)	(0.357)	(0.410)
Lag_Pilot3				0.746*	0.665***	0.848**
				(0.403)	(0.229)	(0.400)
Lag_Charp3				0.204	0.158	0.203
				(0.158)	(0.193)	(0.200)
Lag_Charf3				-0.314	-0.120	-0.268
				(0.234)	(0.259)	(0.262)
Lag_Conve3				0.101	-0.380	0.0176
				(0.357)	(0.398)	(0.379)

Table 10 Continued

	(1) BEVP	(2) BEVP	(3) BEVP	(4) BEVP	(5) BEVP	(6) BEVP
Lag_Subsidies3				-0.00181	-0.114	-0.0361
				(0.0788)	(0.0829)	(0.107)
Lag_Provplan4					1.835***	1.812***
					(0.465)	(0.645)
Lag_Pilot4					0.672**	0.394
					(0.262)	(0.503)
Lag_Charp4					-0.0198	-0.0531
					(0.127)	(0.179)
Lag_Charf4					-0.127	-0.253
					(0.218)	(0.200)
Lag_Conve4					0.280	0.0369
					(0.353)	(0.301)
Lag_Subsidies4					-0.0739	-0.00868
					(0.0630)	(0.0922)
Lag_Provplan5						0.224
						(0.437)
Lag_Pilot5						0.173
						(0.386)
Lag_Charp5						0.126
						(0.193)
Lag_Charf5						0.264
						(0.173)
Lag_Conve5						-0.216
						(0.327)
Lag_Subsidies5						-0.203
						(0.159)
Log (Income)	1.453*	1.205	1.451	1.763	1.754	1.999
	(0.878)	(0.942)	(0.994)	(1.065)	(1.259)	(1.512)
Log (Electricity)	-1.657	1.853	-1.007	-1.878	-7.762	-11.46
	(5.778)	(6.477)	(7.005)	(8.743)	(11.76)	(13.51)
Log (Gasoline)	-0.441	-0.199	0.683	2.579	6.984	5.791
	(3.653)	(3.719)	(4.023)	(4.476)	(4.473)	(5.296)
Log (Population)	21.74*	16.75	22.87	23.43	20.67	15.12
	(12.52)	(13.69)	(15.31)	(17.94)	(20.63)	(19.43)
Constant	-192.7**	-171.7	-209.0	-214.8	-162.0	-90.93
	(97.58)	(111.3)	(128.8)	(150.5)	(164.8)	(148.5)
Observations	1,858	1,621	1,398	1,220	1,069	928
R-squared	0.818	0.836	0.853	0.861	0.870	0.878

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 11 Regression Results of BEVG Subsample with Lag Terms (Lag1-Lag2), 2013-2015.

	(1) BEVG	(2) BEVG	(3) BEVG
Provplan	0.891	0.00657	1.636*
	(0.545)	(0.699)	(0.844)
Pilot	0.752	0.0762	-0.129
	(0.901)	(1.144)	(1.422)
Charp	-0.235	0.426	0.412
	(0.189)	(0.320)	(0.428)
Charf	0.291	0.540*	0.371
	(0.220)	(0.325)	(0.522)
Conve	-0.277	-1.174**	-1.093
	(0.396)	(0.462)	(0.741)
Subsidies	-0.0216	-0.0660	-0.155
	(0.105)	(0.128)	(0.201)
Lag_Provplan1		0.349**	2.849***
		(0.173)	(0.647)
Lag_Pilot1		1.096**	-0.565
		(0.542)	(0.614)
Lag_Charp1		-0.715*	-0.929*
		(0.368)	(0.475)
Lag_Charf1		-0.196	0.592
		(0.357)	(0.392)
Lag_Conve1		0.960*	0.321
		(0.524)	(0.726)
Lag_Subsidies1		-0.0550	-0.0456
		(0.111)	(0.146)
Lag_Provplan2			-2.963***
			(0.690)
Lag_Pilot2			1.447
			(0.909)
Lag_Charp2			0.272
			(0.201)
Lag_Charf2			-0.352
			(0.346)
Lag_Conve2			0.184
			(0.449)
Lag_Subsidies2			-0.203
			(0.131)
Log (Income)	0.0164	-0.210	-0.150
	(1.756)	(1.948)	(2.092)
Log (Electricity)	2.194	7.036	18.96
	(10.44)	(13.40)	(14.44)

Table 11 Continued

	(1) **BEVG**	(2) **BEVG**	(3) **BEVG**
Log (Gasoline)	-9.127*	-4.557	0.991
	(5.151)	(6.159)	(7.171)
Log (Population)	-24.97	-22.90	-36.85
	(17.05)	(23.90)	(30.34)
Constant	206.4*	151.3	181.0
	(124.1)	(187.7)	(236.3)
Observations	1,524	1,262	1,041
R-squared	0.704	0.714	0.713

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 12 Regression Results of PHEVP Subsample with Lag Terms (Lag1-Lag5), 2013-2015.

	(1) **PHEVP**	(2) **PHEVP**	(3) **PHEVP**	(4) **PHEVP**	(5) **PHEVP**	(6) **PHEVP**
Provplan	-0.132**	-0.0466	0.00541	0.0253	0.0607	0.0475
	(0.0574)	(0.0849)	(0.0676)	(0.0692)	(0.0750)	(0.0854)
Pilot	-0.0423	-0.0800	-0.0374	-0.0655	-0.0636	-0.0711
	(0.0543)	(0.0856)	(0.0858)	(0.0896)	(0.0954)	(0.101)
Charp	-0.110*	-0.169	-0.147	-0.0841	-0.104	-0.0827
	(0.0622)	(0.105)	(0.108)	(0.103)	(0.100)	(0.0960)
Charf	0.0456	0.0390	0.0488	0.0162	0.0387	0.0729
	(0.0640)	(0.0914)	(0.0963)	(0.0981)	(0.0898)	(0.0849)
Conve	-0.0457	0.0933	0.125	0.125	0.0552	0.0500
	(0.0807)	(0.156)	(0.148)	(0.153)	(0.155)	(0.150)
Subsidies	0.00717	-0.0136	0.00148	0.0123	0.0161	0.0187
	(0.0118)	(0.0200)	(0.0162)	(0.0166)	(0.0180)	(0.0183)

Table 12 Continued

	(1) PHEVP	(2) PHEVP	(3) PHEVP	(4) PHEVP	(5) PHEVP	(6) PHEVP
Lag_Provplan1		-0.0686	-0.0760	-0.0826	-0.112	-0.0997
		(0.0804)	(0.0808)	(0.0949)	(0.100)	(0.111)
Lag_Pilot1		0.0693	0.0779	0.0472	0.0311	0.0289
		(0.100)	(0.118)	(0.121)	(0.129)	(0.130)
Lag_Charp1		0.0901	-0.0337	-0.124	-0.0478	-0.0461
		(0.116)	(0.119)	(0.138)	(0.125)	(0.121)
Lag_Charf1		0.00336	-0.00939	0.0605	-0.0317	-0.108
		(0.0980)	(0.108)	(0.117)	(0.116)	(0.113)
Lag_Conve1		-0.188	-0.166	-0.182	-0.103	-0.0591
		(0.171)	(0.188)	(0.199)	(0.202)	(0.208)
Lag_Subsidies1		0.0249	-0.000132	8.15e-05	-0.00297	-0.00290
		(0.0205)	(0.0254)	(0.0297)	(0.0316)	(0.0317)
Lag_Provplan2			-0.0622	-0.0378	-0.0104	-0.0503
			(0.0586)	(0.0855)	(0.0855)	(0.0870)
Lag_Pilot2			-0.0558	-0.0707	-0.0806	-0.103
			(0.0742)	(0.0911)	(0.0971)	(0.100)
Lag_Charp2			0.156	0.159	0.0972	0.0854
			(0.116)	(0.134)	(0.116)	(0.118)
Lag_Charf2			-0.0397	-0.0574	0.0187	0.0961
			(0.107)	(0.121)	(0.117)	(0.123)
Lag_Conve2			-0.0592	-0.0291	0.0528	-0.0101
			(0.153)	(0.210)	(0.204)	(0.218)
Lag_Subsidies2			0.00955	-0.00991	-0.0276	-0.0376
			(0.0248)	(0.0257)	(0.0245)	(0.0253)
Lag_Provplan3				-0.0221	0.0394	0.0433
				(0.0872)	(0.120)	(0.117)
Lag_Pilot3				0.0692	0.0237	-0.0333
				(0.0942)	(0.120)	(0.121)
Lag_Charp3				0.0511	0.0572	0.0469
				(0.0943)	(0.108)	(0.112)
Lag_Charf3				-0.0598	0.0645	0.0245
				(0.0756)	(0.107)	(0.115)
Lag_Conve3				-0.0298	-0.341*	-0.222
				(0.180)	(0.204)	(0.205)
Lag_Subsidies3				0.0108	0.00202	-0.00236
				(0.0198)	(0.0222)	(0.0236)
Lag_Provplan4					-0.0976	0.0307
					(0.0724)	(0.0825)
Lag_Pilot4					0.0991	0.226**
					(0.0824)	(0.0975)

Table 12 Continued

	(1) PHEVP	(2) PHEVP	(3) PHEVP	(4) PHEVP	(5) PHEVP	(6) PHEVP
Lag_Charp4					-0.00825	0.0515
					(0.0988)	(0.0818)
Lag_Charf4					-0.165	-0.139
					(0.112)	(0.106)
Lag_Conve4					0.242*	0.179
					(0.127)	(0.150)
Lag_Subsidies4					0.0268*	0.0161
					(0.0161)	(0.0207)
Lag_Provplan5						-0.0979
						(0.0777)
Lag_Pilot5						-0.0732
						(0.0789)
Lag_Charp5						-0.108
						(0.0913)
Lag_Charf5						0.0276
						(0.100)
Lag_Conve5						-0.0547
						(0.125)
Lag_Subsidies5						0.0264
						(0.0189)
Log (Income)	0.317	0.449	0.529	0.643*	0.743*	0.810*
	(0.334)	(0.359)	(0.367)	(0.377)	(0.384)	(0.416)
Log (Electricity)	3.792***	3.670***	3.539**	3.362**	3.535***	3.565**
	(1.339)	(1.295)	(1.396)	(1.357)	(1.305)	(1.424)
Log (Gasoline)	1.031	0.916	1.684	1.695	1.474	1.589
	(0.993)	(1.019)	(1.132)	(1.246)	(1.266)	(1.331)
Log (Population)	-2.501	-2.296	-1.538	-0.867	-0.927	-1.265
	(5.341)	(5.374)	(5.547)	(5.642)	(5.626)	(5.920)
Constant	-14.48	-16.22	-23.82	-29.20	-30.22	-28.27
	(44.73)	(45.30)	(46.74)	(48.06)	(48.33)	(51.07)
Observations	4,138	3,728	3,407	3,120	2,909	2,730
R-squared	0.887	0.890	0.893	0.889	0.890	0.891

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 13 Regression Results of PHEVG Subsample with Lag Terms (Lag1-Lag5), 2013-2015.

	(1) PHEVG	(2) PHEVG	(3) PHEVG	(4) PHEVG	(5) PHEVG	(6) PHEVG
Provplan	-0.0203	0.000207	-0.135	-0.216	-0.266	-0.252
	(0.0620)	(0.0891)	(0.121)	(0.139)	(0.164)	(0.159)
Pilot	0.00317	-0.0644	-0.122	-0.0656	-0.0743	-0.194
	(0.0758)	(0.0982)	(0.118)	(0.130)	(0.143)	(0.186)
Charp	0.206	0.174	0.116	0.0819	0.0146	0.00803
	(0.240)	(0.192)	(0.216)	(0.218)	(0.242)	(0.256)
Charf	-0.0930	-0.0831	-0.0634	-0.0777	-0.201	-0.141
	(0.153)	(0.182)	(0.223)	(0.232)	(0.275)	(0.264)
Conve	-0.0517	-0.0288	0.0133	0.0306	0.0864	0.181
	(0.103)	(0.186)	(0.206)	(0.241)	(0.271)	(0.292)
Subsidies	0.00591	-0.0113	-0.00658	-0.00307	0.00849	-0.0137
	(0.0125)	(0.0234)	(0.0266)	(0.0310)	(0.0325)	(0.0328)
Lag_Provplan1		-0.00691	0.137	0.194	0.209	0.408*
		(0.103)	(0.153)	(0.181)	(0.229)	(0.234)
Lag_Pilot1		-0.00783	0.182	0.101	0.0718	0.0796
		(0.133)	(0.139)	(0.159)	(0.175)	(0.211)
Lag_Charp1		0.177	0.215	0.208	0.198	0.211
		(0.232)	(0.156)	(0.197)	(0.178)	(0.203)
Lag_Charf1		-0.106	0.0733	0.0469	0.148	0.0817
		(0.148)	(0.143)	(0.180)	(0.186)	(0.218)
Lag_Conve1		-0.0156	-0.232	-0.199	-0.207	-0.238
		(0.225)	(0.255)	(0.286)	(0.307)	(0.336)
Lag_Subsidies1		0.0175	0.00270	0.0124	0.00635	0.0232
		(0.0235)	(0.0342)	(0.0387)	(0.0414)	(0.0441)
Lag_Provplan2			-0.0331	-0.132	-0.0601	-0.133
			(0.160)	(0.233)	(0.236)	(0.308)
Lag_Pilot2			-0.173	-0.0329	-0.119	-0.106
			(0.164)	(0.171)	(0.160)	(0.189)
Lag_Charp2			0.0841	0.110	0.145	0.155
			(0.300)	(0.338)	(0.402)	(0.448)
Lag_Charf2			-0.288	-0.361	-0.440	-0.493*
			(0.204)	(0.242)	(0.296)	(0.296)
Lag_Conve2			0.238	0.398	0.342	0.329
			(0.256)	(0.293)	(0.295)	(0.347)
Lag_Subsidies2			0.00903	-0.0328	-0.0357	-0.0249
			(0.0316)	(0.0348)	(0.0377)	(0.0407)
Lag_Provplan3				0.0922	0.104	-0.0248
				(0.115)	(0.163)	(0.226)
Lag_Pilot3				-0.121	0.0253	0.00770
				(0.167)	(0.173)	(0.170)

Table 13 Continued

	(1) PHEVG	(2) PHEVG	(3) PHEVG	(4) PHEVG	(5) PHEVG	(6) PHEVG
Lag_Charp3				-0.0486	-0.0611	-0.0269
				(0.155)	(0.183)	(0.193)
Lag_Charf3				0.141	0.224	0.246
				(0.160)	(0.194)	(0.227)
Lag_Conve3				-0.357*	-0.417	-0.407
				(0.209)	(0.269)	(0.259)
Lag_Subsidies3				0.0497	0.0469*	0.0378
				(0.0315)	(0.0280)	(0.0323)
Lag_Provplan4					0.0180	-0.129
					(0.119)	(0.213)
Lag_Pilot4					-0.0361	0.0436
					(0.196)	(0.159)
Lag_Charp4					0.209	0.0854
					(0.204)	(0.183)
Lag_Charf4					-0.192	-0.105
					(0.182)	(0.213)
Lag_Conve4					-0.00658	0.388
					(0.235)	(0.409)
Lag_Subsidies4					0.00856	-8.54e-05
					(0.0296)	(0.0409)
Lag_Provplan5						0.180
						(0.130)
Lag_Pilot5						0.135
						(0.129)
Lag_Charp5						-0.00579
						(0.367)
Lag_Charf5						-0.0196
						(0.181)
Lag_Conve5						-0.484
						(0.448)
Lag_Subsidies5						-0.00184
						(0.0380)
Log (Income)	0.207	0.757	1.196	1.602	2.153*	2.022*
	(0.642)	(0.784)	(0.845)	(0.998)	(1.141)	(1.208)
Log (Electricity)	1.133	2.294	3.019	3.931	4.295	6.251
	(1.880)	(2.600)	(3.204)	(3.581)	(3.678)	(4.266)
Log (Gasoline)	1.293	1.980	3.150	3.509	4.170	1.742
	(2.792)	(2.859)	(3.320)	(3.491)	(3.640)	(4.178)
Log (Population)	-1.248	0.949	3.401	2.841	2.524	-0.255
	(6.483)	(8.042)	(11.17)	(12.13)	(14.84)	(18.45)

Table 13 Continued

	(1) PHEVG	(2) PHEVG	(3) PHEVG	(4) PHEVG	(5) PHEVG	(6) PHEVG
Constant	-8.689	-40.89	-72.36	-77.74	-83.27	-66.76
	(52.78)	(65.01)	(87.90)	(94.50)	(116.7)	(145.8)
Observations	2,001	1,715	1,484	1,269	1,136	1,012
R-squared	0.773	0.767	0.772	0.769	0.776	0.776

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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