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Abstract:

Governments have been heavily involved in financing investments that provide environmental benefits. The Chinese government has provided various green incentives for the new energy vehicle (NEV) industry. This study evaluates the effectiveness of these low-carbon incentive policies. We estimate a NEV demand model and simulate different policy scenarios. We find that incentive policies have increased the NEV demand by 56.26% during the sample period. Among these incentive policies, free license policy contributed most of the sales. One should, therefore, consider both financial and non-financial incentive policies in future green development program designs.

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Governments have been heavily involved in financing investments that provide environmental benefits. The Chinese government has provided various green incentives for the new energy vehicle (NEV) industry. This study evaluates the effectiveness of these low-carbon incentive policies. We estimate a NEV demand model and simulate different policy scenarios. We find that incentive policies have increased the NEV demand by 56.26% during the sample period. Among these incentive policies, free license policy contributed most of the sales. One should, therefore, consider both financial and non-financial incentive policies in future green development program designs.

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1. Introduction

Green finance, defined as the financing of investments that provide environmental benefits, is discussed more and more frequently since the establishment of the Green Climate Fund (GCF) in 2010 (IFC, 2017; Zhang et al., 2019). Broadly speaking, the green financing tools include green loans, green bonds and other green incentive policies. How these tools performed to mitigate the problem of greenhouse gas (GHG) emissions or transform the non-green industry remains an important research question.

Emission from transportation is one of the most important sources of GHG emissions in the world. China is the largest automotive market in the world since 2009. Emissions generated by vehicles traffic are considered to be a critical factor causing the smog pollution. To reduce the vehicle emissions, China has implemented various policies including adjusting consumption tax and fuel tax rates, introducing stricter emission standards, and a Vehicle Quota System (VQS) in some large cities.

Like many other countries, China also heavily subsidizes the purchase of new energy vehicles (NEVs). China initiated several innovative green finance mechanisms that can be applied to this sector (Du and Ouyang, 2017). The Chinese central government launched a program of green finance in the form of subsidies for NEV purchase. Some local governments have also been supportive of the NEVs sector by offering their own subsidies proportional to that provided by the central government. Apart from subsidies, some local governments have also provided free license plates for NEVs, which is a non-financial incentive policy.[1] This is an extremely supportive measure on the part of those large cities which implemented a license restriction policy, including Beijing, Shanghai, Shenzhen, Guangzhou, Hangzhou and Tianjin. With the support of these policies, China has become the biggest NEV market since 2015.

Comparing to conventional vehicles with internal combustion engines, NEVs can reduce GHG emissions by a considerable amount, especially when driven with frequent stops or long

[1] The VQS is a quantity control policy on vehicles, which makes license plates extremely difficult to obtain in Shanghai.

idling time (Laberteaux and Hamza, 2018). Therefore, how subsidies and free license plate policies, as innovative green finance measures, may stimulate the adoption of NEV is an important empirical research question. Clinton and Steinberg (2019) assess the impact of vehicle purchase subsidies on NEV adoptions in USA. They find that the adoption of NEV would increase by approximately 8% if the subsidy increased by $1000. Qian (2018) evaluates the impacts of the subsidy program using detailed vehicle registration data in China from 2010 to 2015. She finds that 94% of the NEV sales in 2015 were induced by subsidies in 19 big cities. However, Qian (2018) did not consider the impacts of free licenses.

Shanghai has been the largest NEV market in China. The strict VQS also presents an ideal opportunity to study the different impacts of financial subsidies and non-financial incentive policies. Using detailed monthly sales data from 2016-2018, we estimate a random coefficient discrete choice model to estimate the demand function. Through counterfactual analyses, we find that government incentive policies have explained 56.26% of the sales during the sample period. In addition, almost half of the NEV sales were induced by free licensing policy in Shanghai. Moreover, government policies have different impacts on the demand for different types of NEVs.

2. Industry background and data

2.1 Industry background

NEVs can be classified into four types according to its fuel type: Battery-Powered Electric Vehicle (BEV), Extended Range Electric Vehicle (EREV), Plug-In Hybrid Electric Vehicle (PHEV) and Hybrid Electric Vehicle (HEV). A BEV gets all its power from its batteries and electric motors.

An EREV has an auxiliary power unit (called a range extender) which increases the EREV's driving range. A HEV or PHEV uses an electric motor and gas engine to operate.

Ever since Shanghai issued its first private car license plate in 1986, the city has been trying to control the number of private cars on the road. In 1994, the local government set a quota on newly issued licenses, selling them in auctions. As the demand soared, the price of license plates increased dramatically. In recent years, consumers would have to pay for a license plate a price of about RMB 90 thousand ($14,300) for an internal combustion engine vehicle, after winning the auction with a probability of around 5% each month. As an alternative to winning a plate for a non-NEV, consumers can get a free plate if they buy a NEV.

In addition to free licensing, both the central and the Shanghai municipal government have subsidized NEVs according to its type, as shown in Table 1 and Table 2.[2] Many NEVs are entitled to financial subsidies from both central and local government. The government has devoted its financial subsidies mainly to BEVs, next EREVs, and then PHEVs. Meanwhile, the size of the government subsidy began to decrease after 2014.

Table 1: 2016-2018 NEV financial subsidy from the central government (unit: yuan)

	Pure electric mileage: R (Mile)	
	Pure Electric	**Plug-In**

[2] Central subsidy data was collected from "Notice on Financial Support Policies for the Promotion and Application of New Energy Vehicles in 2016-2020", "Notice on Adjustment of Fiscal Subsidy Policy for Promotion and Application of New Energy Vehicles", and "Notice on Adjusting and Improving Fiscal Subsidy Policies for the Promotion and Application of New Energy Vehicles". Local government subsidy data was collected from "Interim Measures of Shanghai Municipality on Encouraging the Purchase and Use of New-Energy Vehicles" and its subsequent adjustments, and "Shanghai Measures for Encouraging the Purchase and Use of New Energy Vehicles".

							Hybrid
Year	100≤R<150	150≤R<200	200≤R<250	250≤R<300	300≤R<400	R≥400	R≥50
2016	25000	45000		55000			30000
2017	20000	36000		44000			24000
Transition period	14000	25200		30800			16800
2018	-	15000	24000	34000	45000	5.0000	22000

Note: The subsidy program in 2018 can be divided into three phases. In the first phase (1^{st} January to 11^{th} February), the subsidy program was the same as 2017. In the second phase (12^{th} February to 11^{th} March), the subsidy program underwent a transition. In the third phase (12^{th} March to 31^{th} December) the program was carried out as the 2018 program.

Table 2: 2016-2018 NEV financial subsidy from Shanghai government (unit: yuan)

	Pure electric mileage: R (Mile)						
	Pure Electric						**Plug-In Hybrid**
Year	100≤R<150	150≤R<200	200≤R<250	250≤R<300	300≤R<400	R≥400	R≥50
2016	10000	30000					10000
2017	10000	18000		22000			10000
Transition period	7000	12600		15400			5040
2018	-	7500	24000	17000	22500	25000	6600

Note: From 2018, the total subsidy amount cannot exceed the 50% of the sales price of a NEV.

2.2 Data

Our data covers the monthly sales of all NEVs in Shanghai from 2016 to mid-2018. During this period, the combined total sales of HEV, BEV, PHEV and EREV in Shanghai are 129,142. Information on the price, quantity and product characteristics of different NEV models is obtained from a market analysis firm. To estimate the consumer demand, we aggregate sales in each month to the car model level, which forms a panel data of 125 car models in 29 months. Because the incentive policies are car model specific, we match our data with the incentive policies manually. The summary statistics for our key variables are reported in Table 3.

Table 3: Summary Statistics of Key Variables

Variable	Mean	Std. Dev.	Min	Max
sales	96.1593	262.8370	1.0000	3004.0000
price (Million)	0.5025	65.6351	5.0300	1338.8000
subsidy (Million)	1.6885	2.6298	0.0000	8.5000
license	0.4758	0.4996	0.0000	1.0000
cost (Yuan/Mile)	0.6003	0.7028	0.0253	3.2683
horsepower	176.8757	110.0549	16.0000	887.0000
weight (Kg)	1757.4690	392.4247	724.0000	2995.0000
HEV	0.3812	0.4859	0.0000	1.0000
BEV	0.2889	0.4534	0.0000	1.0000
PHEV	0.3031	0.4597	0.0000	1.0000

EREV	0.0268	0.1616	0.0000	1.0000

3. NEV Demand model

We use counterfactual analysis to evaluate the effectiveness of the incentive program. To compute the sales change, we need to estimate the demand function and then apply the comparative statics to the equilibrium states with and without these incentive policies.

3.1 Demand function

We estimate the demand function using the Random-Coefficient Demand Model, referred to as the BLP model introduced by Berry et al. (1995). The BLP model has been widely applied in various industries, including the mortgage service (Montes, 2014), mutual fund (Li and Qiu, 2014) and deposit service (Egan et al., 2017).

A market is defined as a NEV market on a monthly basis. In a given month t, household i chooses from J_t vehicle models and an outside good to maximize his utility. The outside good refers to non-NEVs. The indirect utility of household i choosing product j is defined as

$$u_{ijt} = v\left(p_{jt} - s_{jt}, X_{it}, \xi_{jt}\right) + \varepsilon_{ijt} \tag{1}$$

p_{jt} is the vehicle price and s_{jt} is the total subsidy for that product. X_{jt} represents observed product attributes including whether a model enjoys a free license, cost per mile, horsepower and weight. ξ_{jt} is the unobserved product attribute.

The specification of the indirect utility v is assumed thus

$$\mathrm{v}_{ijt} = -\alpha_i(p_{jt} - sub_{jt}) + \sum_k X_{kjt}\tilde{\beta}_{ikt} + \varepsilon_{tj} \quad (2)$$

where $\alpha_i = \bar{\alpha} + \sigma_p v_{it}$, $\sigma_p v_{it}$ captures the consumer heterogeneity in price, v_{it} has a standard normal distribution, and σ_p is the standard deviation of the normal distribution. X_{kjt}, which is the *k*th product attribute of product *j*. $\tilde{\beta}_{ikt}$ stands for consumer heterogeneous taste for attribute k, which is

$$\tilde{\beta}_{ikt} = \bar{\beta}_k + \sigma_k v_{ikt} \quad (3)$$

where $\bar{\beta}_k$ is the mean preference for product attribute k, which is constant across all markets and consumers. v_{ikt} follows a normal distribution and σ_k is its standard deviation, which stands for consumer i's preference for attribute k.

We denote the parameters to be estimated as θ, which equals to (θ_1, θ_2). θ_1 and θ_2 represent linear and nonlinear parameters, respectively. The utility function can be decomposed into a common utility $\delta(\theta_1)$ and a heterogeneous utility $\mu(\theta_2)$.

$$u_{ijt} = \delta_{jt} + \mu_{ijt} + \varepsilon_{ijt} \quad (4)$$

$$\delta_{jt} = \sum_k X_{jkt}\bar{\beta}_k + \xi_{jt} \quad (5)$$

$$\mu_{ijt} = -\alpha_i(p_{jt} - sub_{jt}) + \sum_k X_{jkt}\sigma_k v_{ikt} \quad (6)$$

Household i chooses the vehicle with the highest utility. Let κ_i be the vector of unobserved individual attributes. The market share of product j is given by

$$s_{jt}(p, X, \xi, y_i; \theta_2) = \int \frac{\exp(v_{ijt})}{1+\sum_{l=1}^{J_t}\exp(v_{ilt})} dF(\kappa) \quad (7)$$

The market share of outside option can be calculated as $s_0 = \frac{1}{1+\sum_{l=1}^{J_t} \exp(v_{ilt})}$. We define the total vehicle sales (NEV and non-NEV) as the market size.

3.2 Identification

By matching the observed market shares and predicted market shares in Equation (7), we can estimate the model parameters. Since integration is not feasible, the integral is approximated by the following equation:

$$s_{jt} = \frac{1}{ns} \sum_{i=1}^{ns} \frac{\exp(v_{ijt})}{1+\sum_{l=1}^{J_t} \exp(v_{ilt})} \quad (8)$$

We estimate the parameters in the mean utility with the generalized method of moments (GMM). The moment conditions come from the assumption that the unobservable characteristic, ξ_{jt}, is mean independent from the instruments.

Due to the correlation between the unobserved product attribute and price, we will use the product's own observed characteristics, such as cost, weight, type dummy and horsepower, the sum of characteristics of the other products produced by the same firm, and the sum of characteristics of products produced by the other firms as instrumental variables to address the endogeneity problem. The assumption that the instruments are uncorrelated with unobservable attributes provides the moment condition:

$$\mathrm{E}\left(\xi_{jt}(\theta_1, \theta_2) \middle| Z_{jt}\right) = 0 \quad (9)$$

where the unobserved individual attributes have been integrated over in equation (7), and Z_{jt} includes all excluded and exogenous instruments. We follow a recent trend of using the

Mathematical Program with Equilibrium Constraints (MPEC) method to estimate the demand model (Dubé et al., 2012).

4. Estimation Results

We assume consumers to have heterogeneous preferences on price and product attributes. The estimation results are in Table 4. The average price elasticity ($\bar{\alpha}$) is -0.0222 and significant. Free license and horsepower are positively related to consumers' utility.

The random coefficients stand for the standard deviation of household preferences from the mean for vehicle attributes. The significant positive estimate of standard deviation of price coefficient indicates that there remains significant unobserved demographic heterogeneity, which may include the purpose of use, types of family, and so on.

Table 4: Results from the random coefficient model

Variable	Mean	Std. Dev.
price	-0.0222**	0.0081***
	(0.0106)	(0.0008)
lic	1.0652*	0.0234***
	(0.9105)	(0.0031)
cost	-0.5727**	0.2513*
	(0.2702)	(0.1362)
hp_weight	1.4678***	5.7457***
	(0.5598)	(0.6927)

constant	-8.9299***	0.0250***
	(3.3487)	(0.0037)

Note: The asymptotically robust standard errors of estimates are shown in parenthesis. Significant levels: *p<0.1, **p<0.05, ***p<0.01.

5. Counterfactual

To evaluate the effectiveness of these incentive policies, we simulate the counterfactual equilibrium state without incentive policies.

5.1 Sales without subsidy and free licensing

We simulate the NEV demand quantity under three policy scenarios: 1) withdrawing both financial subsidies and the free licensing policy; 2) withdrawing financial subsidies but keeping free licensing; 3) keeping financial subsidies but not free licensing. For each scenario, we adjust our price and license data under each policy regime, then use our estimated demand model to simulate the market shares of each product and the sales.

In the first scenario, withdrawing all incentives will lead to a reduction of 72,652 (56.26%) NEV adoptions, while only cancelling free licensing policy would decrease the demand by 69,862 (54.10%) NEVs. Only withdrawing the financial subsidies could cut the NEV demand by 7,017 NEVs (5.43%).

The result shows that the “free license” policy was responsible for almost half of the NEV sales in Shanghai, while the effect of financial subsidies is quite limited. Free licensing with NEVs saves consumers both money and trouble, which proves to be extremely important in consumers’ vehicle purchase decisions.

5.2 Sales change of four types of NEVs

We further calculate sales change for each of the four different types of NEVs (EREV, BEV, PHEV and HEV) under the three policy scenarios. Recall that the government incentives are much greater for BEV and PHEV. The simulated sales changes are shown in Table 5. Without any incentive policy, the sales of PHEV and BEV will decrease by 61.91% and 64.80%, respectively. Meanwhile, sales of EREV and HEV remains stable in this scenario. Overall, government policies significantly stimulated the demand for PHEV and BEV, but not so much for EREV and HEV.

Table 5: Sales change of four types of NEV

Type	Sales	sub=0 and lic=0		sub=0 and lic=1		sub=1 and lic=0	
		Change	Percentage	Change	Percentage	Change	Percentage
EREV	790	-41	-5.21%	0	0.02%	-41	-5.21%
BEV	26,655	-17,272	-64.80%	-1,849	-6.94%	-16,571	-62.17%
HEV	14,877	519	3.49%	50	0.33%	500	3.36%
PHEV	86,820	-53,750	-61.91%	-5,218	-6.01%	-55,858	-64.34%
Total	129,142	72,652	-56.26%	7,017	-5.43%	69,862	-54.10%

6. Conclusion and policy implications

Government investments in green energy projects may be crucial to achieving the SDGs.

Both the central and Shanghai municipal government in China have devoted substantial funding and other incentive policies to increase the development of the NEV industry. This paper evaluated the effectiveness of the NEV incentive policies in Shanghai.

We estimated a BLP model to recover consumers' preference on different NEV models. Based on our demand model, we simulated different policy scenarios and found that government incentive policies have greatly increased the NEV demand by 56.26% during the sample period. Among these incentive policies, free license contributed most to the sales. Based on our results, the government should keep the free license policy, and should speed up the phasing-out of financial subsidies, which we show have not been such an effective policy tool. The implication for developing future green development programs is that one needs to consider not only financial but also non-financial incentive policies.

Reference

Berry, S., Levinsohn, J., Pakes, A., 1995. Automobile prices in market equilibrium. *Econometrica*.: 63 (4), 841–890.

Clinton, B.C., Steinberg D.C., 2019. Providing the Spark: Impact of financial incentives on battery electric vehicle adoption. *Journal of Environmental Economics and Management* 98, 1–18.

Dubé, J. P., Fox, J. T., Su, C. L. (2012). Improving the numerical performance of static and dynamic aggregate discrete choice random coefficients demand estimation. *Econometrica*, 80(5), 2231-2267.

Du, J., Ouyang, D., 2017. Progress of Chinese electric vehicles industrialization in 2015: A review. *Applied Energy*. 188, 529-546.

Egan, M., Hortaçsu, A., & Matvos, G. (2017). Deposit competition and financial fragility: Evidence from the us banking sector. *American Economic Review*, 107(1), 169-216.

IFC., 2017. *Green Finance: a Bottom-Up Approach to Track Existing Flows*. International Finance Corporation., Washington, D.C.

Laberteaux, K.P., Hamza K., 2018. A study on opportune reduction in greenhouse gas emissions via adoption of electric drive vehicles in light duty vehicle fleets. *Transportation Research* Part D. 63, 839–854.

Li, S., & Qiu, J. (2014). Financial product differentiation over the state space in the mutual fund industry. *Management Science*, 60(2), 508-520.

Montes, C.P., 2014. The effect on competition of banking sector consolidation following the financial crisis of 2008. *Journal of Banking & Finance*, *43*, pp.124-136.

Qian, J., 2018, *Evaluating the electric vehicle subsidy program in China*, Cornell University working paper.

Zhang, D., Zhang, Z., Managi, S., 2019. A bibliometric analysis on green finance: current status, development, and future directions. *Finance Research Lett*ers 2019, 425-430.