

Does Open Source Pay off in the Plug-in Hybrid and Electric Vehicle Industry? A Study of Tesla's Open-Source Initiative

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Abstract

In June 2014, Tesla, a leading manufacturer of electric vehicles, announced it would make its software and hardware available for free to other automakers. This paper analyzes the effect of Tesla's open source initiative on the plug-in hybrid and electric vehicle (PHEV) industry in the US. On the one hand, open source allows PHEV manufacturers to use the advanced technology of Tesla, which could lead to lower investment costs and a higher incentive to invest. Open source also partially removes the entry barriers and could attract more entrants and induce economies of scale, leading to decreased manufacturing costs. On the other hand, underinvestment of Tesla's rivals may occur as a result of free riding, which could result in slower quality improvements in the industry. I quantify these impacts by estimating a dynamic structural model, where players make investment and entry decisions to maximize discounted future returns. My results show that Tesla's initiative was beneficial for the industry and Tesla. I find a 60% drop in investment cost, and a decrease of 100 million in entry cost into the PHEV industry. Counterfactual analysis shows that, had Tesla not provided open source, the industry would have had 33% fewer PHEVs and Tesla would have had \$400 million less in profit.

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1 Introduction

Does technology sharing contribute to the development of a newly emerging industry? To what extent will that positive effect be? In June 2014, the CEO of Tesla, one of the major manufacturers of electric vehicles, Elon Musk made a surprise announcement: *"in the spirit of the open-source movement, the wall of Tesla patents has been removed for the advancement of electric vehicle technology"*.¹ What effect has this open source initiative had on this newly emerging industry and on Tesla? These are the questions at the forefront of this research paper.

It may seem obvious that the open source initiative could only have a positive impact. However, in reality, it may generate different impacts on the development of the plug-in hybrid and electric vehicle (PHEV) industry, as well as on the open source firm – Tesla. On the one hand, it allows rivals to get access to Tesla's more advanced technology without cost, and hence decreases the cost of investment. On the other hand, Tesla's rivals lose the incentive to develop new technology, which could result in underinvestment in this newly emerging industry. Furthermore, as Tesla's patents reveal the technology and the costs that potential entrants need to enter the PHEV industry, the entry barriers are partly removed, leading to industry expansion. Thus, the demand for the PHEV-specific accessories and mechanical components increases and induces economies of scale for the upstream firms. The reduction of manufacturing costs could further lead to a decrease in prices.

The effect of open source on Tesla itself is also not obvious. Rivals' investments on the follow-up innovation of Tesla's technology may have a spillover effect on Tesla.² As Tesla is more familiar with its own technology that they shared with competitors, it would also have a higher probability of successfully adopting the follow-up innovation of its competitors (?). However, Tesla may be worse off if it faces fiercer competition due to open source resulting in more PHEV competitors.

To capture the various impacts of open source mentioned above, I develop and estimate a dynamic structural oligopoly model in the spirit of ?, where I incorporate entry and investment decisions of each PHEV and allow marginal manufacturing costs to depend on the number of active PHEVs. PHEVs choose investments to improve quality, which leads to higher profits in the product market, where they compete with conventional counterpart-

¹Elon Musk, 'All Our patents Belong to You', Tesla Motors, 12 June 2014, <https://www.tesla.com/blog/all-our-patent-are-belong-you>

²Rivals' follow-up innovation based on Tesla's technology has to be open as well.

ners. PHEVs are assumed to make entry and investment decisions based on the current industry state – the quality distribution of PHEVs, and their private shocks in entry and investment costs, which leads to a Markov-perfect Nash equilibrium.

To estimate the model, I use data from several sources. The information on sales, prices and characteristics of both PHEVs and conventional cars allow me to estimate the demand parameters.³ With these parameters, I construct quality measures of all PHEVs based on their characteristics from 2012 to 2017. I follow a two-step estimation procedure (à la ?) to recover the investment and entry costs that determine the dynamics of the PHEV industry.⁴ In the first step, I estimate the parameters that characterize the equilibrium behaviors of PHEVs. In the second step, I find the structural parameters, entry and investment costs, that maintain the optimality of the estimated behaviors. Those estimates are recovered before and after Tesla’s open source initiative.

My research contributes to the literature of open source by quantifying the different effects of open source using a structural model. Previous research mainly focuses on understanding the incentive of programmers to contribute to open source software (???) or incentive of firms to provide open source software (????)⁵ mainly in a qualitative way. I extend the study on open source to a more complex industry and one that includes hardware.

I also contribute to the literature on the adoption of alternative-energy vehicles, where most study incentives on the consumer side (????), or the network effect of charging stations (?). ? and ? both find a positive impact of higher gasoline prices, income tax reduction of hybrid car drivers and other non-monetary incentives on the adoption of alternative-fuel vehicles. ? find federal income tax credit program for EV buyers will result in an increase in both EV sales and charging stations, leading to feedback loops and amplifying the demand incentive. Rather than studying the effectiveness of incentive on demand side, I focus on how car producers change their innovation behavior when the supply side environment changes, and that in turn results in changes of purchase decision of consumers.

My paper is also related to the growing literature of empirical analysis on industry

³I follow the classical discrete-choice literature (???)

⁴The two-step estimation is introduced by ? into the single-agent dynamic model and extended by ?? into dynamic games.

⁵? find that programmers use the contribution to open source software as a signal for productivity. ? suggests that one benefit of using open source is that making code available to everyone induces the sophisticated end-users to debug and to improve the quality of the software.

dynamics. Deviating from ?, ? and ? where firms/players are assumed to be homogeneous, I use a richer demand side specification where consumers choose from heterogeneous products.

I find that investment costs and entry costs both decrease dramatically after open source. Unit investment cost drops from around \$17 million to \$6.5 million. The PHEV entrants had to pay \$555 to \$595 million to enter the industry prior to the open source initiative, while post-open-source the entry cost distribution shifts to \$460 to \$520 million. My results also show that marginal costs of production decrease with the number of active PHEVs, confirming the existence of economies of scale in the industry.

One interesting question is what would have happened in the absence of Tesla’s open source initiative. I examine that by using my estimates to conduct a counterfactual analysis in a world, where Tesla does not share the technology with its competitors. I find that without the open source initiative, the number of PHEVs in the industry drops by 33% due to high entry costs. I also find that Tesla’s discounted future returns decreases from \$61 million to -\$348 million. My results show that open source was beneficial to the PHEV industry on the whole.

The rest of the paper is organized as follows. Section 2 introduces the PHEV industry briefly and the relevant data. In section 3, I describe the theoretical model. In section 4, I present the estimation technique and the results are shown in section 5. I discuss counterfactuals in section 6 and conclude in section 7.

2 Industry and Data

2.1 Electric and plug-in hybrid vehicle industry

The production of electric vehicles (EV) can be traced back to the 1830s. A number of pioneers including Anyos Jedlik, Robert Anderson and Tomas Davenport produced separately the small-scale electric cars using non-rechargeable batteries. For a long while, EVs were more popular than gasoline vehicles. However, due to the increasing discovery of crude oil, advanced technology in gasoline motors and mass production, gasoline cars started outselling EVs in 1910.

The EV industry came back to life only after people started to pay attention to the increasingly severe air pollution situation and limited fuel reserves. The recovery was first led by hybrid electric vehicles (HEVs). Honda Insight was released in 1999 and it was

the first mass-produced hybrid model. Though the hybrid electric vehicle has a motor combining gas and electric powertrain, it still relies heavily on fuel as the battery onboard can only be recharged from gas. Then followed the plug-in hybrid vehicles (PHVs), whose representative is Chevrolet Volt produced by GM, with Toyota and Ford models coming after. PHV uses rechargeable batteries and can be recharged by plugging into an external electricity source. Once the stored electricity is used up, its gasoline-powered engine is activated which also generates electricity to recharge the battery. The battery electric vehicles (EVs) rely purely on battery power with no backup fuel source. Tesla Roadster is the first mass-produced highway-capable all-electric sports car and Nissan Leaf is the first EV produced for families.

Now most large car manufacturers⁶ are involved in the production of plug-in hybrid and electric vehicles (PHEVs), which includes PHVs and EVs, and total sales of PHEVs past 1.5 million in June 2016⁷. However, the market share of PHEVs remains considerably small. Among the top-10 PHEV adopting countries in 2015, while Norway and the Netherlands had a remarkable market share of 9.74% and 22.39%, respectively⁸, the remaining only had market shares ranging from 0.35% (in Canada) to 2.62% (in Sweden). This low market share could in part be due to the prohibitively high prices of PHEVs and to the limited driving range compared to traditional gasoline cars (?), which may be improved by access to better technology.

In this paper, I focus on PHEVs, as these two types of cars can potentially benefit the most from the open source initiative of Tesla. PHEV use battery as their main energy source, which is almost 40% of the total cost of a PHEV. Approximately 60% of Tesla's patent is related to the battery and charging system. Thus, the PHEVs can directly benefit from the advanced technology of Tesla, especially Tesla's small-format battery packages, which are much cheaper than the large-format used by other automakers. However, there are only a few suppliers of PHEVs' batteries and they all suffer from small-scale of production and, hence, the price remains considerably high. Larger demand for the battery and other mechanical components could induce economies of scale of production and also lead to more intense competition among suppliers. Thus, the manufacturing costs of PHEVs

⁶Manufacturers as Audi, BMW, Ford, Honda, Mercedes-Benz, Mitsubishi, Nissan, Porsche, Toyota, Volkswagen, and Volvo all provide at least one PHEV by 2017.

⁷Jeff Cobb, 'Global Plug-in Car Sales Cruise Past 1.5 Million', HybridCars, 22 June 2016, <http://www.hybridcars.com/global-plug-in-car-sales-cruise-past-1-5-million/>

⁸Jeff Cobb, 'Top Six Plug-in Vehicle Adopting Countries - 2015', HybridCars, 18 January 2016, <http://www.hybridcars.com/top-six-plug-in-vehicle-adopting-countries-2015>

could eventually decrease and as a consequence, also the prices. With lower purchase prices and the consideration of environmental issues, consumers may be more willing to buy PHEVs. The larger market size benefits all PHEV-producers, and Tesla with its advanced technology and better cars may be in a position to gain a higher market share and obtain higher profits. In addition, as Tesla is more familiar with its own technology, even though all other automakers use its patent and adopt its technology, Tesla may be more efficient to produce the similar electric cars and bear a lower production cost than its rivals as a result.

Moreover, a direct monetary cost of giving up patents is insignificant for Tesla as cross-licensing in the auto industry is considerably rare⁹. The car manufacturers patent their innovation mostly out of the consideration of secrecy and preventing litigation rather than of direct monetary return. Furthermore, the firms need to pay annual renewal fees to maintain the patent and to litigate any patent infringement, which is costly and time-consuming.

2.2 Data

My data cover the automobile industry in the U.S. from 2012 to 2017 and come from a variety of sources. The monthly sales (in quantity) of essentially all PHEV models marketed in the US from January 2012 to December 2017 come from *hybridcars.com*. I complement these with sales data from *WardsAuto U.S. light vehicle sales*, which covers conventional cars (and a portion of the PHEVs) from January 2012 until August 2015. I aggregate the sales data at the quarter level.

I obtain the physical attributes and manufacturer's suggested retail price of each baseline car model from *MSNAutos* websites via web-scraping, where the data are provided by *JATO Dynamics*. Prices are in 2012 dollars. The physical attributes are size, horsepower per weight, range on highway, fuel economy, cargo volume and a dummy variable for whether navigation is standard equipment. Another dummy variable for whether a car is a PHEV is constructed by checking the fuel type. Size is defined as length times width, which measures the "footprint" of a vehicle. Horsepower per weight provides a proxy for the power of the engine/motor. Range on highway is the maximum distance a conventional car can reach on highway with its tank fully filled, or a EV fully charged. For PHV, it is the

⁹Steve Brachmann, 'Ford patent licensing announcement may signal end of NIH bias in auto industry', IPWatchdog, 9 June 2015, <http://www.ipwatchdog.com/2015/06/09/ford-patent-licensing-end-of-nih/id=58476/>

combination of the range with gasoline/diesel and the range with electricity. Fuel economy is defined as miles per gallon (MPG) for conventional cars, as miles per gallon-equivalent electricity (MPGe) for EVs, and as combined MPG and MPGe for PHVs, i.e. total range/ (range with gasoline/MPG + range with electricity/MPGe)¹⁰.

In addition to those standard physical characteristics, I use APEAL (Automotive Performance, Execution and Layout), a survey from *JD-Power*, and an owner satisfaction survey from *Consumer Reports* to construct a subjective measure of consumers evaluation of performance and design (PD) for each model. In both surveys, consumer are asked to give opinions regarding driving experience, comfort, styling, and the entertainment system. More specifically, the evaluation captures how consumers enjoy the acceleration of the car, whether the seats are comfortable, whether they can easily control the navigation/audio system, etc. This measure ranges from 1 to 5.

I combine the sales data with the price and characteristics (physical and subjective) to construct my final datasets. The first dataset contains observations of both conventional cars and PHEVs from 2012Q1 to 2015Q2. I use this part of the data to identify the price sensitivity and the taste parameters that the consumers attach with each characteristic, when consumers make purchase decision with both conventional cars and PHEVs in their choice set. The inclusion of the data of conventional cars gives more variation on sales and characteristics, and hence, allow me to obtain more accurate result in estimating the taste parameters.

The second dataset only contains information of PHEVs from the year 2012 to the year 2017. I assume that consumers evaluate the characteristics in the same fashion among conventional cars and PHEVs, and those evaluations are consistent throughout the year 2012 to the year 2017. Under these assumptions, I apply the evaluation of characteristics obtained from the first dataset on the PHEVs and form the quality measure of each model. In this way, I obtain the evolution of each PHEV's quality and, hence, the development of the whole PHEV industry. I use this dataset to perform the analysis of the dynamic supply side, where PHEVs make entry and investment decisions.

Table 1 shows the average sales-weighted prices and characteristics of conventional cars, PHVs and EVs from the first dataset. I consider the combination of a model-quarter as an observation. In total, I obtain 3159 observations with 278 distinct car models, including 10 PHVs and 13 EVs. As shown in table 1, the main differences between the conventional cars

¹⁰In some cases information on fuel economy and maximum driving range on highway were missing,. In these cases I collected them manually from *Fueleconomy.gov*.

and PHEVs are prices, fuel economy and driving range on highway. PHEVs have relatively higher prices and shorter maximal range than the conventional ones, while conventional cars have very low fuel efficiency. The power of all types of cars, which is represented by Horsepower/weight, and subjective measure of performance and design (PD) do not seem significantly different from one to another.

Table 1: Comparison of average (sales-weighted) characteristics

	Price	HP/Weight	MPG(e)	Range (Highway)	PD
Gasoline/Diesel	Obs: 2965				
Mean	24.88	0.57	2.51	5.00	3.28
Std	9.92	0.11	0.60	0.81	0.90
Min	10.85	0.36	1.2	2.9	1
Max	114.2	1.89	5	9.5	5
Plug-in Hybrid	Obs: 80				
Mean	35.97	0.44	4.18	4.68	3.88
Std	11.57	0.08	0.54	0.84	0.83
Min	28.84	0.39	2.23	3.3	3
Max	132.43	1.03	5.05	5.7	5
Electric	Obs: 114				
Mean	39.98	0.49	10.72	1.12	3.44
Std	15.54	0.22	1.08	0.49	0.61
Min	22.11	0.25	7.6	0.62	2
Max	67.81	0.81	12.4	2.08	4

Price is in \$1000, HP/Weight is horsepower per 10 lbs., MPG(e) is tens of miles per gallon, Range (Highway) is in 100 miles, PD is performance and design.

Table 2 shows the evolution of the PHEV industry from beginning of 2012 to the end of 2017. In the first panel, I present the average sales-weighted prices and characteristics of PHVs. The prices fluctuate within the range of \$35,000 to \$37,000 with an increasing standard deviation, indicating the variety of available PHVs increases over time. Horsepower/weight and range on highway both show an increasing trend, while miles per gallon decreases slightly. The second panel shows the changes in prices and characteristics of EVs. Prices increase over time and all characteristics experience some improvements. It is also noticeable, that there are new entrants every year in both categories, while there are very few exiting PHEVs.

Table 3 gives a comparison among PHVs and among EVs before and after open source.

Table 2: Average (Sales-Weighted) Characteristics for PHEVs, 2012-2017

Plug-in Hybrid	2012	2013	2014	2015	2016	2017
Price	36.1 (3.43)	35.8 (4.07)	34.9 (10.3)	35.7 (11.9)	37.1 (13.0)	35.4 (13.5)
Horsepower/Weight	0.41 (0.031)	0.43 (0.049)	0.46 (0.093)	0.47 (0.09)	0.50 (0.10)	0.50 (0.13)
Miles Per Gallon	4.29 (0.53)	4.21 (0.49)	4.15 (0.56)	3.92 (0.54)	3.91 (0.79)	4.14 (0.98)
Range on Highway	4.43 (0.79)	4.68 (0.83)	4.84 (0.83)	4.76 (0.83)	4.86 (0.82)	5.11 (1.09)
No. PHV Model	3	7	10	14	18	24
Entry	2	4	3	4	5	7
Exit	0	0	0	0	1	1

Electric	2012	2013	2014	2015	2016	2017
Price (in \$1000)	39.2 (8.74)	41.0 (14.6)	39.6 (16.6)	44.3 (17.5)	50.2 (18.6)	48.6 (17.3)
Horsepower/Weight	0.41 (0.20)	0.53 (0.23)	0.48 (0.21)	0.55 (0.22)	0.54 (0.14)	0.55 (0.13)
MPG/MPGe	9.87 (0.48)	10.5 (1.08)	10.9 (1.07)	10.8 (1.16)	10.4 (1.16)	10.5 (1.20)
Range on Highway	1.09 (0.75)	1.01 (0.31)	1.21 (0.54)	1.37 (0.57)	1.57 (0.58)	1.77 (0.56)
No. EV Model	6	9	12	12	13	16
Entry	4	3	4	1	1	3
Exit	0	0	1	1	0	0

Price is in \$1000, HP/Weight is horsepower per 10 lbs., MPG(e) is tens of miles per gallon, Range (Highway) is in 100 miles.

I show the average (sales-weighted) characteristics and prices within 10 periods before and after the announcement of the open source initiative. The first two columns in category PHV presents the characteristics of the PHV models that are in the industry before the open source initiative, which I refer to as PHV incumbent. The comparison between these two columns shows how the same models change their characteristics over time. The PHV incumbents experience a price drop after open source with all characteristics, except fuel economy (MPG/MPGe) and subjective measure on performance and design, improves slightly. In the third column are the PHV entrants, which are the PHVs introduced in

the market after open source. Compared to column one, the PHV entrants enter with significantly higher prices, but also provide overall better configurations. I divide EVs into three groups following the same classification: EV incumbents before open source, EV incumbents after open source and the EV entrants. Among EV incumbents, I observe an increase in prices and that characteristics evolution shares a similar trend as the PHVs, with range on highway increasing substantially. EV entrants also enter with higher prices but overall better qualities.

Table 3: Comparison of Characteristics Before and After Open Source

	PHV			EV		
	Incumbents Before OS	After OS	Entrants After OS	Incumbents Before OS	After OS	Entrants After OS
	average (sales-weighted) characteristics					
Price	35.23 (5.91)	32.33 (6.99)	45.11 (18.20)	40.19 (14.68)	45.61 (17.48)	52.72 (19.12)
Size	1.26 (0.06)	1.32 (0.08)	1.47 (0.15)	1.28 (0.20)	1.28 (0.23)	1.41 (0.22)
Horsepower/weight	0.43 (0.05)	0.46 (0.06)	0.56 (0.15)	0.49 (0.22)	0.55 (0.18)	0.52 (0.12)
Range on highway	4.66 (0.82)	4.83 (0.78)	5.13 (1.09)	1.07 (0.48)	1.45 (0.58)	1.76 (0.55)
MPG/MPGe	4.24 (0.53)	4.16 (0.38)	3.60 (1.21)	10.51 (1.03)	10.68 (1.16)	10.32 (1.18)
Performance and design	4.1 (0.82)	3.16 (0.65)	3.7 (0.65)	3.6 (0.52)	3.27 (0.95)	4.1 (0.41)
Total Sales	116,777	44,923	108,425	90,331	48,712	153,992
Entry	6		12	8		5
Exit	0		1	0		2
No. Model	7		17	10		13

Total sales of both PHV incumbents and EV incumbents decrease, even though the observed physical characteristics becomes overall better. The fall in sales of incumbents may be driven by the decreased subjective evaluation on performance and design, as well as the fiercer competition in the product market. I observe more entrants in PHVs, while less in EVs. Exit is only observed after open source.

3 Model

I build my dynamic structural model on the work of ?. There are maximum N plug-in hybrid and electric vehicles being active in the industry. PHEVs are differentiated by quality levels ω_j . Time is discrete with infinite horizon and PHEVs discount the future at the rate $\beta = 0.925$. In each period, the sequence of events unfolds as follows: first, potential PHEV entrants observe the private random entry costs and decide on entry. Simultaneously, one of the lowest-quality PHEV incumbents may face an exogenous shock and exit the industry. Then, the remaining PHEV incumbents receive choice-specific shocks on investment and make decisions on whether to invest or not. Third, PHEV incumbents compete with conventional cars in the product market and collect profits. Finally, both entry and investment decisions are carried out at the end of the period and state (quality) of PHEVs evolves accordingly.

I discuss these components in turn.

3.1 Demand

I specify demand using a discrete-choice model (?), where consumers can choose among a PHEV, a conventional car or an outside option, which includes not purchasing a car or purchasing a car outside of the 278 models considered. Let u_{ij} denote the utility consumer i receives from purchasing car model j :

$$u_{ij} = \sum_{h=1}^H \alpha_h z_{hj} - \alpha_0 p_j + \eta_j + \epsilon_{ij}, \quad (1)$$

where z_{hj} represents the h -th car observable characteristics (discussed in section 2.2), p_j is the price, η_j is an unobserved product characteristics, and ϵ_{ij} is an idiosyncratic taste shock following a Type-I Extreme Value distribution. These shocks are independently and identically distributed across consumers and products. I assume each consumer purchases at most one car in each period (???). The utility from the outside option u_{i0} is normalized to be zero. I use data from 2012Q1 to 2015Q3, which contains both information of conventional cars and PHEVs to identify the taste parameters α_h and price parameter α_0 .

Similar to ?, I define each car's absolute quality as

$$q_j = \sum_{h=1}^H \alpha_h z_{hj} + \eta_j. \quad (2)$$

In this way, I simplify the cars' heterogeneity from several dimensions to only one. I further follow ? and discretize the absolute quality q_j into quality levels denoted by ω_j . These are state variables of each car, that enter the dynamic model. I discuss this in more details in section 5.1.2.

Consumers choose the cars give them the highest utility. The market share of car model j is given by

$$s_j = \frac{\exp(q_j - \alpha_0 p_j)}{1 + \sum_{\omega_k \neq 0} \exp(q_k - \alpha_0 p_k)}. \quad (3)$$

3.2 Supply of Incumbents

Each car manufacturer can sell multiple car models. The profit of a multi-product manufacturer f , who is in the market, is given by

$$\pi_f(\mathbf{p}, \mathbf{q}, \boldsymbol{\omega}) = \sum_{j \in J_f} \pi_j(\mathbf{p}, \mathbf{q}, \boldsymbol{\omega}) = \sum_{j \in J_f} s_j(\mathbf{p}, \mathbf{q}) M[p_j - c_j(\boldsymbol{\omega})], \quad (4)$$

where J_f is the set of cars that manufacturer f provides, \mathbf{p} is the vector of prices, \mathbf{q} is the vector of qualities, $\boldsymbol{\omega}$ is the vector of quality levels, $s_j(\mathbf{p}, \mathbf{q})$ is given by equation 4 and M is the market size. Market size is defined as the number of household in the whole US of that period less the number of registered car in the last period.

The marginal cost of car model j is given by

$$c_j(\boldsymbol{\omega}) = \begin{cases} \gamma_0 \omega_j + v_j & \text{if } j \text{ is conventional car,} \\ \gamma_0 \omega_j + \gamma_1 (\sum_{j=1}^N \mathbf{1}(PHEV_j = 1)) + v_j & \text{if } j \text{ is PHEV.} \end{cases} \quad (5)$$

For both conventional cars and PHEVs, the marginal cost depends on the quality levels ω_j . For the PHEVs, the cost additionally depends on the total number of active PHEVs in the market, where γ_1 measures the effect of economies of scale. The v_j is an unobserved component (for econometrician), which also affects the manufacturing cost.

In order to maximize the overall profit, a multi-product manufacturer sets the prices

to satisfy the first-order conditions

$$\frac{\partial \pi_f}{\partial p_j} = M \left(s_j + \sum_{k \in J_f} (p_k - c_k(\boldsymbol{\omega})) \frac{\partial s_k(\mathbf{p}, \mathbf{q}, \boldsymbol{\omega})}{\partial p_j} \right) = 0 \text{ for all } j \in J_f. \quad (6)$$

In the dynamic supply side of the model, PHEVs may change their qualities depending on their investment decisions. Investment is a discrete choice $x_j^t \in \{0, 1\}$. PHEV incumbents make their investment decisions after observing private choice-specific shocks, $\phi_j^t(x_j^t)$, which are independent and identically distributed according to the Type I extreme value distribution. PHEV j obtains a per-period payoff

$$\tilde{\pi}_j^t(\boldsymbol{\omega}^t) + C(\omega_j)x_j^t + \phi_j^t(x_j^t), \quad (7)$$

where $\tilde{\pi}_j^t(\boldsymbol{\omega}^t)$ is the maximized profit from the static product market competition and $C(\omega_j)$ denotes the state-dependent investment cost, which is paid only if the PHEV j decided to invest. I specify the investment cost as

$$C(\omega_j) = \bar{c}\omega_j^2 \quad (8)$$

Conditional on investing, PHEVs face stochastic investment outcomes $\tau_j^t = \{0, 1, 2\}$, meaning the quality of a PHEV can stay the same, increase by one unit or increase by two units, respectively. Those outcomes take place with the following probabilities:

$$p(\tau_j^t = 2 | x_j^t = 1) = p_2 + \lambda_2 \mathbb{1}(OS_j = 1), \quad (9)$$

$$p(\tau_j^t = 1 | x_j^t = 1) = p_1 + \lambda_1 \mathbb{1}(OS_j = 1), \quad (10)$$

$$p(\tau_j^t = 0 | x_j^t = 1) = 1 - p(\tau_j^t = 1 | x_j^t = 1) - p(\tau_j^t = 2 | x_j^t = 1), \quad (11)$$

where OS_j indicates that PHEV j belongs to the open-source firm Tesla, and λ_1, λ_2 are parameters to estimate that allow an innovation advantage of the open source firm. If a PHEV decides not to invest, then the quality drops by one with probability one in the next period.

Once the investment outcomes are realized, the state evolves according to:

$$\omega_j^{t+1} = \omega_j^t + \tau_j^t \mathbb{1}(x_j^t = 1) - \mathbb{1}(x_j^t = 0). \quad (12)$$

I assumed when a PHEV already reaches the highest possible quality level, it can no longer have a successful investment and when a PHEV has the lowest quality level, it will no longer suffer a quality drop even if it does not invest. I make these assumptions to avoid explosion of the state space.

3.3 Potential Entrants

PHEVs with zero quality level are considered as potential entrants. In each period, I allow five potential PHEV entrants with randomly drawn quality levels to arrive¹¹. Let $\phi_j^{(e)t}$ denote the private random entry cost of potential PHEV entrant j in period t . Entry costs are independently and identically distributed across potential PHEV entrants and periods according to a distribution $F^e(\cdot)$. An entry decision is denoted as

$$\chi_j^t(\boldsymbol{\omega}^t, \phi_j^{(e)t}) \in \{0, 1\}, \quad (13)$$

where $\chi_j^t(\boldsymbol{\omega}^t, \phi_j^{(e)t}) = 1$ indicates that potential entrant j draws entry cost $\phi_j^{(e)t}$ and decides to enter the market, given the industry state is $\boldsymbol{\omega}^t$, and $\chi_j^t(\boldsymbol{\omega}^t, \phi_j^{(e)t}) = 0$ otherwise. However, entrant j will not participate in the product market competition at time t , but use this whole period to set up the production line with payment $\phi_j^{(e)t}$ and become an incumbent in the next period $t + 1$. It also cannot make investment decision in this period. Unlike the incumbents, potential entrants are short-lived and do not take the discounted future return into account. If potential entrants do not enter the industry, they receive nothing and vanish. As entry cost is private information, the entry decision of a potential PHEV entrant is viewed as random by its rivals. Therefore, I formulate

$$\xi_j^{(e)t}(\boldsymbol{\omega}^t) \equiv \text{prob}(\chi_j^t(\boldsymbol{\omega}^t, \phi_j^{(e)t}) = 1) = \int \chi_j^t(\boldsymbol{\omega}^t, \phi_j^{(e)t}) dF^e(\phi_j^e) \quad (14)$$

to represent the probability that a potential PHEV entrant j enters the market with the industry state $\boldsymbol{\omega}^t$.

3.4 Exit

I assume exit is an exogenous event, which is motivated by rare exit occurrence that I observe in the data. The constant probability of such an event taking place is denoted

¹¹The assumption on the amount of potential entrants is motivated by data. I observe on average two entrants per period, with the maximum being four.

as ψ . Only the incumbents with the lowest quality may face this event. Furthermore, I assume only one incumbent can exit in each period. If more than one incumbent has the lowest-quality level, each of them exits with the same probability. For instance, if there are four incumbents in quality level one, then each of them has a probability of $\psi/4$ to exit. Furthermore, I assume that any PHEV will only leave the market after at least 10 periods.

3.5 Equilibrium

In each period t , PHEV j makes entry, investment and pricing decisions to maximize its discounted future returns. PHEVs anticipate the product market competition when they make entry and investment decisions, as the states (qualities) are publicly observable.

Let $V_j^t(\boldsymbol{\omega}^t, \phi_j^t)$ denote the value function of incumbent PHEV j :

$$V_j^t(\boldsymbol{\omega}^t, \phi_j^t) = \max_{x_j^t \in \{0,1\}} \left\{ \tilde{\pi}_j^t(\boldsymbol{\omega}^t) + C(\omega_j)x_j^t + \phi_j^t(x_j^t) \right. \\ \left. + \beta E\{V_j^{t+1}(\boldsymbol{\omega}^{t+1}, \phi_j^{t+1}) | \boldsymbol{\omega}^t, \omega_j^{t+1} \neq 0, x_j^t(\boldsymbol{\omega}^t), x_{-j}^t(\boldsymbol{\omega}^t), \xi_{-j}^t(\boldsymbol{\omega}^t)\} \right\} \quad (15)$$

where $\tilde{\pi}_j^t(\boldsymbol{\omega}^t)$ is the maximized profit from the static product market competition, C denotes the investment cost, $\phi_j^t(x_j^t)$ is the investment-choice-specific shock, $\xi_{-j}^t(\boldsymbol{\omega}^t)$ and $x_{-j}^t(\boldsymbol{\omega}^t)$ represent the entry and investment decisions of competitors.

Potential PHEV entrants must weigh the benefits of entering against their draws of entry costs. They face the similar value function except the fact that they do not have per-period payoff and do not make investments in the period that they enter. Let $V_j^{(e)t}(\boldsymbol{\omega}^{(e)t}, \phi_j^{(e)t})$ denote the value function of potential entrant j :

$$V_j^{(e)t}(\boldsymbol{\omega}^t, \phi_j^{(e)t}) = \max_{\chi_j^{(e)t} \in \{0,1\}} \left\{ \chi_j^{(e)t} \right. \\ \left. \left(-\phi_j^{(e)t} + \beta E\{V_j^{(e)t+1}(\boldsymbol{\omega}^{t+1}, \phi_j^{(e)t+1}) | \boldsymbol{\omega}^t, \omega_j^{t+1} \neq 0, \xi_{-j}^{(e)t}(\boldsymbol{\omega}^t), x_{-j}^{(e)t}(\boldsymbol{\omega}^t)\} \right) \right\} \quad (16)$$

where $\chi_j^{(e)t}$ is entry choice and $\phi_j^{(e)t}$ is the random entry cost.

I assume PHEVs use symmetric strategies that depend solely on the current industry state and their randomly drawn entry costs/choice-specific shocks, leading to a Markov-Perfect Nash Equilibrium (??).

Let σ_j denote the strategy used by PHEV j , which represents entry decisions of poten-

tial entrants and investment decisions of incumbents. MPNE requires that each PHEV’s strategy is optimal given the strategies of its competitors:

$$V_j(\boldsymbol{\omega}, \phi_j; \sigma_j, \sigma_{-j}) \geq V_j(\boldsymbol{\omega}, \phi_j; \sigma', \sigma_{-j}), \quad (17)$$

for all PHEV j , all states $\boldsymbol{\omega}$, all shocks ϕ and all possible alternative strategies σ' . The private shocks guarantee that at least one equilibrium in pure strategies exists (?).

4 Estimation

Following ?, I estimate the parameters in two steps. In the first stage, I recover the parameters of the static demand part and estimate the equilibrium policy functions. More specifically, I 1) estimate taste parameters based on consumers’ purchase decisions (see equation 1) and construct the discretized quality level for each car model using those estimates (see equation 2), 2) infer marginal costs from the car model’s first-order condition for optimal pricing (see equation 6), and 3) estimate state transition parameters and policy functions that characterize the investment and entry behavior of car models conditional on their own state and the industry state (see equation 9).

In the second step, I recover the investment cost and the entry cost by imposing the optimality condition of the PHEV’s investment and entry decisions (see equation 17). I 1) forward simulate industry paths based on the theoretical model and use the estimates obtained from the first step to construct equilibrium value functions, and 2) find the parameters such that profitable deviations from the estimated optimal policies are minimized.

4.1 First stage estimation

4.1.1 Consumer demand and quality

In order to back out the taste parameter of each characteristics of cars, I estimate the following equation

$$\ln(s_{jt}) - \ln(s_{0t}) = \sum_{h=1}^H \alpha_h z_{hjt} - \alpha_0 p_{jt} + \eta_{jt}, \quad (18)$$

where s_j is the market share of the car model j given in equation 3 and s_0 is the market share of the outside good. In addition to the physical attributes and the subjective measure on performance and design, I also include brand dummies to control for the fixed effect

of car manufacturers and use time trend variables to control for the industry-wide time fixed-effects. The latter one capture the development of PHEV-specific infrastructure as well¹².

If car manufacturers know the values of the unobserved product characteristics η_{jt} , even though we as econometrician do not, then prices are likely to be correlated with them. In order to control for these potential correlation, I use the set of instruments proposed by ?. These BLP instruments include characteristics of the interested car itself, the sum of characteristics of the models produced by the same manufacturer (exclude itself) and the sum of characteristics of the models from rival brands. I classify all car models into their market segments and performed these operations within segments for additional variation. The intuition of these instruments are from the pricing behavior: car models that have close substitutes will tend to have low markups and car manufacturer respond differently to own and to rivals' products.

The absolute quality is defined as the sum of observed characteristics weighted by the taste parameter and unobserved quality, as shown in equation 2. I then discretize them into quality level ω_j .

4.1.2 Marginal cost

Multi-product car manufacturers choose the set of prices to maximize their overall profits as described in equation 6. I first define a J by J matrix Δ , where the (j, k) element is given by

$$\Delta_{jk} = \begin{cases} \frac{-\partial s_k}{\partial p_j}, & \text{if } k \text{ and } j \text{ are produced by the same manufacturer;} \\ 0, & \text{otherwise.} \end{cases} \quad (19)$$

Solving for the first-order conditions gives:

$$c_j = p_j - \Delta(\mathbf{p}, \boldsymbol{\omega})^{-1} s(\mathbf{p}, \boldsymbol{\omega}) \quad (20)$$

¹²I also added the number of PHEV charging stations to capture this PHEV-specific infrastructure effect. However, the estimate shows that the effect is already nicely picked up by the time trend variable. Thus, that specification is not included.

Then, I parameterize these inferred costs to quantify the impact of quality level and the effect of economies of scale on production costs:

$$\begin{aligned}
 c_j(\boldsymbol{\omega}) &= p_j - \Delta(\mathbf{p}, \boldsymbol{\omega})^{-1} s(\mathbf{p}, \boldsymbol{\omega}) \\
 &= \gamma_0 \omega_j + \gamma_1 \left(\sum_{j=1}^N \mathbb{1}(PHEV_j = 1) \right) + v_j
 \end{aligned}
 \tag{21}$$

where ω_j is the quality level of car model j and the sum is the number of PHEVs in a given time period.

As the unobservables v_j can be potentially correlated with the quality level ω_j , I apply the same set of instruments as discussed in section 4.1.1.

4.1.3 Quality transition

I use forward simulation to construct the endogenous distribution of quality levels by aggregating individual car quality. The evolution of individual cars' states and the distribution of cars' states are characterized by the investment policy function and the stochastic investment outcome.

4.1.4 Investment and entry policy functions

The investment decision depends not only on own PHEV's quality level, but also on the the distribution of quality levels of the whole industry. The distribution is described by a vector of numbers, indicating how many rival models are in a given quality range. I nonparametricly estimate the investment decision.

Similar as the investment decision, the entry decision also depends on the potential PHEV entrant's quality level and the quality distribution of the industry. I nonparametricly estimate both the number of entrants of a given distribution of quality levels and the probability of an entrant with a certain quality type that would enter a given industry structure.

4.2 Second stage estimation: recovering the structural parameters

I follow the methodology proposed by ? and use forward simulation to estimate the investment cost and entry cost distribution. I first construct the ex-ante equilibrium value

function, before its private shocks are realized, as

$$V(\sigma, \theta) = E \left[\sum_{t=0}^{\infty} \beta^t (\tilde{\pi}_j^t(\boldsymbol{\omega}^t) - C(\omega_j) x_j^t(\boldsymbol{\omega}^t) + \phi^t(x_j^t)) | \omega^0 \right], \quad (22)$$

where σ is the estimated investment policy function, $\tilde{\pi}_j^t(\boldsymbol{\omega}^t)$ is the equilibrium profit from demand market, $\boldsymbol{\omega}^t$ is the distribution of quality levels in period t , $C(\omega_j) = \bar{c} \omega_j^2$ is the investment cost and ω_0 is the quality level of the interested car model at the first period of the forward simulation.

Then, I follow ? by rewriting the value function as the inner product of two vectors and get

$$\begin{aligned} V(\sigma, \theta) &= E \left[\sum_{t=0}^{\infty} \beta^t [\tilde{\pi}_j^t(\boldsymbol{\omega}^t) \quad \omega_j^2 x_j^t(\boldsymbol{\omega}^t) \quad \phi^t(x_j^t)] | \omega^0 \right] \cdot \theta \\ &= \left[E \left[\sum_{t=0}^{\infty} \beta^t \tilde{\pi}_j^t(\boldsymbol{\omega}^t) | \omega^0 \right] \quad E \left[\sum_{t=0}^{\infty} \beta^t \omega_j^2 x_j^t(\boldsymbol{\omega}^t) | \omega^0 \right] \quad E \left[\sum_{t=0}^{\infty} \beta^t \phi^t(x_j^t) | \omega^0 \right] \right] \cdot \theta \\ &= [W^1 \quad W^2 \quad W^3] \cdot \theta, \end{aligned}$$

where $\theta = [1 \quad \bar{c} \quad 1]$. W^1, W^2 are generated according to the demand estimation and estimation of the investment policy function. Using the same formula, I obtain the perturbed value functions by perturbing the policy function, denoted as $V(\sigma', \theta) = [\tilde{W}^1 \quad \tilde{W}^2 \quad \tilde{W}^3] \cdot \theta$, where σ' is the perturbed investment behavior.

Finally, I use a minimum distance estimator to determine the unit investment cost that satisfies $V(\sigma, \theta) \geq V(\sigma', \theta), \forall \sigma'$.

$$\hat{\theta} = \arg \min_{\theta} \frac{1}{n} \sum (\min\{V(\sigma, \theta) - V(\sigma', \theta), 0\})^2$$

After the investment cost is estimated, I compute the ex-ante value functions for all potential entrants in different industry structures and estimate the entry probability following the first-stage estimation. In this way, I infer the entry cost distribution by observing the value of potential entrants that indeed enter.

5 Results

In this section, I discuss the results from the first- and second-stage estimation. I start by providing the taste parameters from the demand side, and present the constructed quality levels of each PHEV model. The marginal cost is recovered from the first-order condition of the PHEV producers, and I then show the relationship between the costs and the quality levels. Then, I discuss my results for the quality level transition probabilities, exogenous exit rates and the policy functions both pre- and post- open source initiative.

For the second stage, I first present the investment cost estimated from the simulated value function and the optimality condition of the players' investment problem. Then, I show the distribution of entry costs with the help of the estimated policy functions and the estimated investment cost.

5.1 First-stage estimates

5.1.1 Demand estimates

The estimation results of the taste parameters are shown in table 4 using the instrument described in section 4.1.1. In the first three specifications, I use different ways to capture the time fixed effect. I use year dummies in the first specification, while in the second and third ones I use quarter-level time trend variable and year-level time trend variable, respectively. The results show that the estimates of taste parameters remain almost unchanged across different specifications. Overall, the parameters have the expected signs. The coefficients for price and PHEV dummies are negative and significant. Consumers dislike to pay more for their cars and the negative estimate of PHEV dummy indicates the reluctant attitude towards PHEV, even taking the higher fuel economy and shorter driving range into account. The coefficient signs for product characteristics are all positive. That shows consumers prefer cars with larger size, higher engine/motor power, higher fuel efficiency, larger cargo capacity and longer driving range. Consumers also like navigation as standard equipment and cars with nicer design and better performance.

In the last two specifications, I use PHV and EV dummies separately instead of using only one PHEV dummy. The results show that once I separate those two dummies, the positive effect of MPG/MPGe on consumer utilities vanishes. The reason is that EVs usually have substantially higher MPGe than the PHVs and conventional cars. The estimate for EV dummy captures then not only the consumers' attitude towards this type of car,

Table 4: Demand Estimation

	(1)	(2)	(3)	(4)	(5)
Price	-0.134*** (0.0120)	-0.136*** (0.0121)	-0.135*** (0.0119)	-0.134*** (0.0122)	-0.133*** (0.0120)
Size (L*W)	5.128*** (0.475)	5.208*** (0.480)	5.142*** (0.473)	4.797*** (0.552)	4.742*** (0.546)
Horsepower/Weight	1.286*** (0.351)	1.337*** (0.355)	1.303*** (0.351)	1.201*** (0.365)	1.174*** (0.361)
MPG/MPGe	0.0973*** (0.0350)	0.0929*** (0.0352)	0.0949*** (0.0351)	-0.0167 (0.0630)	-0.0162 (0.0628)
Cargo Volume	0.251*** (0.0353)	0.252*** (0.0357)	0.250*** (0.0354)	0.238*** (0.0357)	0.237*** (0.0354)
Navigation	1.068*** (0.170)	1.091*** (0.173)	1.068*** (0.170)	1.055*** (0.174)	1.038*** (0.171)
Range on Highway	0.194*** (0.0416)	0.187*** (0.0416)	0.191*** (0.0414)	0.249*** (0.0543)	0.253*** (0.0539)
Overall Performance and Design	0.196*** (0.0265)	0.197*** (0.0267)	0.195*** (0.0265)	0.200*** (0.0265)	0.199*** (0.0264)
PHEV	-1.560*** (0.250)	-1.530*** (0.252)	-1.553*** (0.250)		
time trend (quarter)		-0.0126** (0.00582)		-0.0123** (0.00573)	
time trend (year)			-0.0496** (0.0228)		-0.0480** (0.0225)
PHV				-1.474*** (0.253)	-1.492*** (0.251)
EV				-0.424 (0.588)	-0.433 (0.587)
Constant	-14.42*** (0.473)	-14.45*** (0.475)	-14.40*** (0.470)	-13.92*** (0.578)	-13.88*** (0.572)
year dummies	Yes	No	No	No	No
brand dummies	Yes	Yes	Yes	Yes	Yes
Observations	3159	3159	3159	3159	3159
Adjusted R^2	0.351	0.344	0.350	0.352	0.357

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

but also the preference on fuel economy, yielding a biased result. Thus, I should not use the separate dummies.

I use specification (2) for the further estimation of the dynamic model, as it accounts for all possible forces accurately.

5.1.2 Quality levels and quality changes

After constructing the PHEV quality as the sum of characteristics and their corresponding taste estimates, I discretize the quality into six quality levels. The cutoffs are 25 percentile, 50 percentile, 75 percentile, 85 percentile, and 95 percentile. I choose those cutoffs to ensure that car models in each quality level will have more or less the same probabilities to perform successful investment. As lower quality cars are easier to improve than the high-end cars, I impose larger quality intervals for the first three levels than the last three¹³.

Table 5 shows the distributions of PHEV models before and after Tesla’s open source initiative. I find a significant increase in the number of PHEVs in high-quality groups after open source. That could be driven by two different reasons: 1) Tesla’s shared technology helps to remove entry barriers for potential entrants with higher quality, or 2) rivals invest more due to the decreased investment cost induced by open source movement and move to higher quality levels.

Table 5: Quality Levels

	Before OS		After OS		Total	
	Freq.	Percent	Freq.	Percent	Freq.	Percent
0	33	28.70	90	23.75	123	24.90
1	27	23.48	98	25.86	125	25.30
2	37	32.17	86	22.69	123	24.90
3	8	6.96	41	10.82	49	9.92
4	8	6.96	42	11.08	50	10.12
5	2	1.74	22	5.80	24	4.86
Total	115	100.00	379	100.00	494	100.00

Tables 6 and 7 show the transitions between quality levels before and after open source, conditional on investing. Quality levels of the current period are on the vertical axis, whereas the quality levels of the next period are displayed on the horizontal side. The number indicates how many car models’ qualities remain the same or increase after investing. As assumed, if a player invests, then its quality level can either improve or remain the

¹³I experimented with different cut-off points.

same. Thus, there are only positive numbers above the diagonal. The comparison between these two tables shows that low-quality cars have a higher success rate of investment before open source, while high-quality cars have a higher success rate after open source. As Tesla produces only high-quality cars, it suggests that the closer the rivals are with Tesla, the stronger the spillover effect is from open source.

Table 6: Transition matrix conditional on Investment (Before OS)

Quality	Quality Next Period						Total
	1	2	3	4	5	6	
	Freq./(<i>Perc.</i>)	Freq./(<i>Perc.</i>)	Freq./(<i>Perc.</i>)	Freq./(<i>Perc.</i>)	Freq./(<i>Perc.</i>)	Freq./(<i>Perc.</i>)	Freq./(<i>Perc.</i>)
1	28 (84.85)	4 (12.12)	1 (3.03)	0 (0.00)	0 (0.00)	0 (0.00)	33 (100.00)
2	0 (0.00)	16 (66.67)	7 (29.17)	1 (4.17)	0 (0.00)	0 (0.00)	24 (100.00)
3	0 (0.00)	0 (0.00)	29 (90.63)	2 (6.25)	1 (3.13)	0 (0.00)	32 (100.00)
4	0 (0.00)	0 (0.00)	0 (0.00)	5 (83.33)	1 (16.67)	0 (0.00)	6 (100.00)
5	0 (0.00)	0 (0.00)	0 (0.00)	0 (0.00)	7 (87.50)	1 (12.50)	8 (100.00)
6	0 (0.00)	0 (0.00)	0 (0.00)	0 (0.00)	0 (0.00)	2 (100.00)	2 (100.00)

Table 7: Transition matrix conditional on Investment (After OS)

Quality	Quality Next Period						Total
	1	2	3	4	5	6	
	Freq./(<i>Perc.</i>)	Freq./(<i>Perc.</i>)	Freq./(<i>Perc.</i>)	Freq./(<i>Perc.</i>)	Freq./(<i>Perc.</i>)	Freq./(<i>Perc.</i>)	Freq./(<i>Perc.</i>)
1	62 (83.78)	11 (14.86)	1 (1.35)	0 (0.00)	0 (0.00)	0 (0.00)	74 (100.00)
2	0 (0.00)	63 (84.00)	11 (14.67)	1 (1.33)	0 (0.00)	0 (0.00)	75 (100.00)
3	0 (0.00)	0 (0.00)	57 (86.36)	9 (13.64)	0 (0.00)	0 (0.00)	66 (100.00)
4	0 (0.00)	0 (0.00)	0 (0.00)	22 (75.86)	7 (24.14)	0 (0.00)	29 (100.00)
5	0 (0.00)	0 (0.00)	0 (0.00)	0 (0.00)	26 (81.25)	6 (18.75)	32 (100.00)
6	0 (0.00)	0 (0.00)	0 (0.00)	0 (0.00)	0 (0.00)	15 (100.00)	15 (100.00)

5.1.3 Marginal cost

After I obtain the taste parameter estimates and construct the quality levels, I back out the marginal cost of each car model. Recall that marginal cost of a PHEV is computed as:

$c(\omega) = \gamma_0\omega_j + \gamma_1(\sum_{j=1}^N \mathbf{1}(PHEV_j = 1)) + v_j$. The estimation results are in table 8.

Table 8: Marginal Cost

	(1)	(2)	(3)	(4)
	OLS		IV	
Quality	6.069*** (0.367)	5.966*** (0.365)	4.547*** (0.578)	4.706*** (0.518)
No. PHEV Model		-0.125*** (0.0420)		-0.158*** (0.0288)
Constant	13.02*** (2.572)	17.18*** (2.905)	16.99*** (1.826)	21.32*** (2.058)
Brand dummies	Yes	Yes	Yes	Yes
Observations	484	484	429	429
Adjusted R^2	0.867	0.869	0.879	0.885

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The first two columns show the results from OLS estimation, while the last two columns introduce instruments to account for endogeneity of prices. Controlling for brand fixed effects, higher quality yields higher marginal cost, which is intuitive. And the coefficient of the number of active players in the industry (γ_1) being negative confirms the existence of the economies of scales effect.

5.1.4 State transitions and policy functions

The state transition probabilities are determined by the success rates. PHEVs can enjoy at most two units of improvement in quality, conditional on investing. The estimation results are shown in table 9. These results suggest that the success rates of both one-unit and two-unit improvement do not differ prior to the open source initiative and after¹⁴. Tesla does have a premium on one-unit quality improvements before open source, but afterwards, this premium fades away. For the probability of two-unit improvements, Tesla does not differ significantly from its rivals.

I do not observe any exits before Tesla’s open source event. Therefore, the exit probability is simply zero, which is in line with the assumption that player will only leave the market after at least 10 periods, which corresponds to two and a half years. After open

¹⁴For now, I assume high-quality and low-quality players have the same success rates for the reason of tractability.

source, each player faces an exogenous exit probability of 7.7%, if she is active in the industry for more than 10 periods.

Table 9: Transition

	Before OS		After OS	
	Est.	SD	Est.	SD
Prob. of one-unit quality improvement	0.1639	0.0384	0.1577	0.0134
Prob. of two-unit quality improvement	0.0109	0.0064	0.0082	0.0057
Tesla's Premium on one-unit improvment	0.2536	0.1569	0.0329	0.1030
Tesla's Premium on two-unit improvment	-0.0083	0.0089	0.0193	0.0498
Exit prob.	-	-	0.0863	0.0149

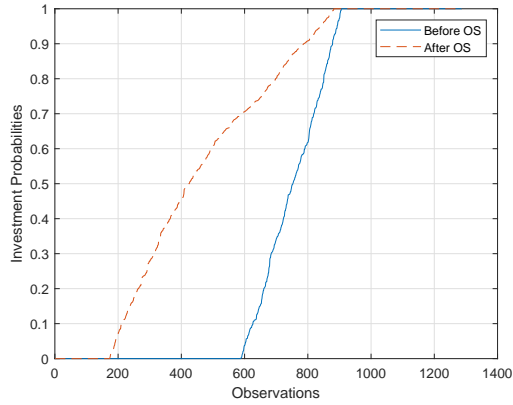
The standard deviations are conducted by bootstrapping.

I use local linear nonparametric regressions to estimate the policy functions, i.e. the investment decisions of the incumbents and the entry decisions of the potential entrants. The regressors in both cases are the focal player's quality level and the quality level distribution of the rivals. For example, a vector of regressors of [3,4,7,2,0,0,0] indicates the focal player is in quality level 3, four of her rivals are in quality level 1, seven of them are in quality level 2 and two of them are in quality level 3. Whereas there are no players in quality levels 4 to 7. Due to the extremely large number of possible industry structures in my exercise, I cannot predict investment and entry probability of all possible states. In figure 1, I show the predicted investment probabilities of each PHEV in randomly selected 500 industry structures. The blue line shows the investment probabilities without open source, while the red dashed line represents the choice after open source. The result shows that in general, PHEV are more likely to invest after open source.

5.2 Second-stage estimates

In the second-stage estimation, I conduct forward simulation to obtain the equilibrium value functions. Using the estimates from the first stage, I compute the per-period profit

Figure 1: Comparison in Investments



of each player. I then simulate the evolution path of the industry, where all players follow the equilibrium policy functions.

As shown in table 10, investment cost decreases after open source from \$16.68 million per quarter to \$6.51 million, by almost 61%. This implies a very strong effect of technological spillovers of Tesla on all its rivals.

Table 10: Investment Cost

	Before OS		After OS	
	Est.	SD	Est.	SD
Investment cost (\$ in millions)	-16.68	4.368	-6.51	2.077

Standard deviation obtained by bootstrap

To determine if these estimates are reasonable, I compute the total investment cost of five brands: BMW, Ford, Mercedes, Tesla and Volvo based on their PHEV's quality levels and their investment decisions in the last quarter of 2017. The results are in table 11. Then I compare the estimated total investment with reported R&D spending that I

obtained from news articles^{15,16,17,18} and Tesla’s annual reports. The reported R&D are on the annual level, I assume the spending is equally divided for each quarter. For BMW and Ford, the estimated investment costs are lower than the reported ones, as the reported R&D spending includes not only the investment in the production of electric vehicles but also in autonomous driving. For Mercedes-Benz, Tesla and Volvo, my estimated results are reasonably close to the reported spending.

Figures 2 and 3 show the distribution of potential entrants’ value before and after open source. The blue lines are the estimated values, and the red dashed lines show the 95% confidential intervals. The left graph shows that the potential entrants with a value lower than approximately \$550 million will not enter the industry, while the entrants with an expected future return of \$600 million will definitely enter. This allows me to infer the entry cost prior to the open source initiative, which is distributed almost linearly between \$555 million and \$595 million. The same argument goes for the right graph. The entry cost after open source is distributed between \$460 million to \$520 million. These findings suggest Tesla’s open source initiative served to partially remove the barriers to entry to the PHEV industry.

6 Counterfactual simulation

I use my estimated parameters and model to predict how the PHEV industry would have evolved, if the open source initiative of Tesla did not occur. I take the observed industry structure in 2014 quarter 3 as the starting structure for the simulation. In this starting period, the 18 active PHEVs are mainly concentrated in the low quality levels: 5 PHEVs belong to quality level one, 4 to level two, 6 to level three, and only 2 and 1 to quality levels five and six, respectively. Each PHEV makes its discrete investment decision and the

¹⁵Edward Taylor, ‘BMW raises R&D spending for electric, autonomous cars’, Reuters, 21 March 2018, <https://de.reuters.com/article/us-bmw-results-outlook/bmw-raises-rd-spending-for-electric-autonomous-cars-idUKKBN1GX0YU>.

¹⁶Matthew DeBord, ‘Ford just made a \$4.5 billion investment to completely transform its business’, Business Insider, 3 January 2017, <https://www.businessinsider.de/ford-45-billion-investment-autonomous-vehicles-2017-1?r=US&IR=T>.

¹⁷Steve Hanley, ‘Mercedes To Bump Electric Car Investment In US By \$1 Billion, Expand Partnership With BYD’, CleanTechnica, 22 September 2017, <https://cleantechnica.com/2017/09/22/mercedes-bump-electric-car-investment-us-1-billion-expand-partnership-byd/>.

¹⁸Esha Vaish, Volvo expects electric car margins to match conventional vehicles by 2025, Reuters, 20 March 2019, <https://www.reuters.com/article/us-volvocars-electric-margins/volvo-expects-electric-car-margins-to-match-conventional-vehicles-by-2025-idUSKCN1R12DD>.

Table 11: Estimated investment real VS. R&D spending in 2017Q4 (\$ in million)

Brand	Model	quality level	Investment cost (with $\bar{c} = 6.51$)	real R&D
BMW	330e	3	58.6233	
	530e	4	104.2192	
	740e	5	162.8425	
	X5	4	104.2192	
	i3	3	58.6233	
	Total			488.5275
Ford	C-Max Energi PHEV	2	26.0548	
	Focus Electric	1	6.5137	
	Fusion Energi PHEV	2	26.0548	
	Total		58.6233	225
Mercedes	B-Class Electric	2	26.05	
	C350e	3	58.62	
	GLE550e	3	58.62	
	S550 Plug in	6	234.49	
	Total		377.79	250
Tesla	Model 3	1	6.51	
	Model S	6	234.49	
	Model X	6	234.49	
	Total		475.50	344.5
Volvo	S90 T8 PHEV	1	6.51	
	XC60 PHEV	3	58.62	
	XC90 T8 PHEV	4	104.22	
	Total		169.36	250

potential entrant decided on entry according to the estimated equilibrium policy functions. I forward simulate the industry structure till 2017, quarter 4 – the last period I observe in the data. I compare the quality distribution of the PHEV under these two scenarios: one without open source and one with open source. The result is shown in figure 4.

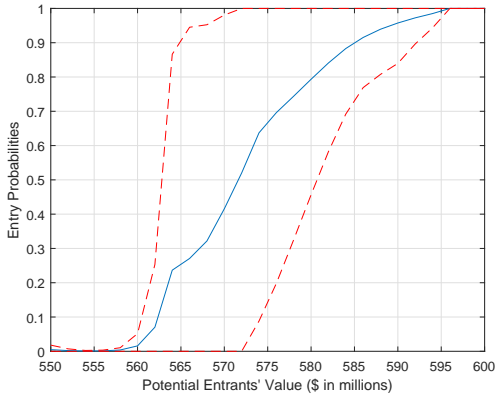


Figure 2: Before Open Source

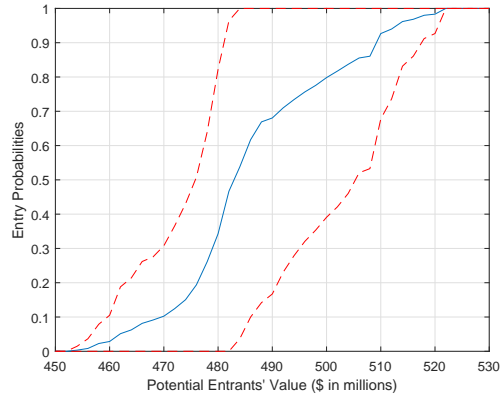
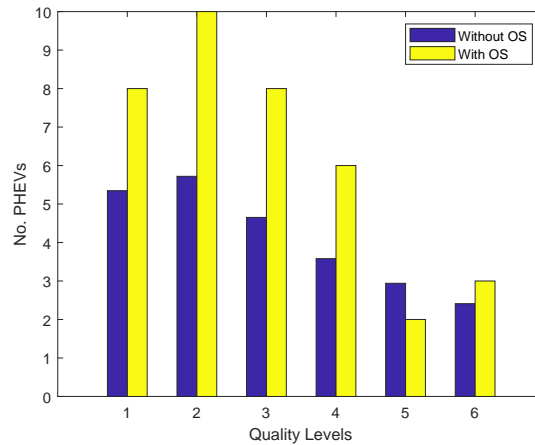


Figure 3: After Open Source

Figure 4: Quality Level Distribution of PHEVs in 2017 Q4



The dark blue bar represents the quality distribution of PHEVs without Tesla opening its technology. The light yellow bar shows the quality distribution that I observed from the data. I repeat the forward simulation 500 times and report the average number of active PHEVs at each quality level. I observe on average 24.6 active PHEVs at the end of 2017 in my simulation, with a standard deviation of 4.45, which is significantly lower than the real amount (37) of PHEVs that I observe from the data. As shown in the graph, more PHEVs are active with the help of open source in all quality levels, except level five. In general, open source allows more low-quality PHEVs to enter the market. It could be explained by

the fact, that PHEVs with lower quality are more sensitive about the decrease in entry cost, because their expected future returns are lower than those entering with higher quality.

I use the same exercise to explore the potential benefits for Tesla from open source. With the same forward simulation procedure, I obtain per-period payoffs (profit minus the investment cost) of Tesla and calculate the discount present value from the point of view of 2014 Q3. The result shows that Tesla has a negative present value (-\$348 million), if the industry would have evolved without open source. Then, using the observed price, sales and the estimated investment cost with open source, I calculate the real discount present value of Tesla, which is +\$ 61 million. This analysis indicates that even though the market competition increased, Tesla still benefited from its open source initiative. The main reason is the substantially lower investment cost induced by open source.

7 Conclusion

I propose a structural dynamic model to quantify the impact of open source on the development of the plug-in hybrid and electric vehicle industry in the US. In particular, I estimate the fixed investment cost and entry cost distribution before and after the open source initiative of Tesla took place. I find the investment cost decreases after open source, which gives incentive for PHEV makers to invest more frequently. That in turn results in producing PHEVs with higher quality. The entry cost also becomes lower after open source, allowing more PHEV models to enter the industry and inducing economies of scale to decrease the manufacturing cost. Overall, my findings suggest that open source had a positive effect on the evolution of the PHEV industry.

Counterfactual experiments suggest substantial underdevelopment of the PHEV industry without open source. In the simulated scenario, where the open source of Tesla is not implemented, the number of PHEVs decreases from 37 to around 25, by 33%. Moreover, according to the behaviors simulated in the counterfactual case, Tesla's present discount payoff becomes negative, while that value is positive given the investment decision that I observed from data. That implies, the effect of a lower investment cost due to open source on Tesla's payoff exceeds the negative impact of fiercer market competition.

The existing literature of open source provides mostly qualitative evaluation of open source, whereas I take advantage of a structural model and am able to disentangle and quantify the different forces of benefits coming along with open source. The modeling and the estimation procedure can be easily adapted in other newly emerging industries to study

the benefit of open source or other kinds of information sharing behavior.