Discussion Paper Series – CRC TR 224

Discussion Paper No. 218
Project B 02

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

Yihan Yan [1]

October 2020

[1] Center for Doctoral Studies in Economics, University of Mannheim, Germany (email: yihan.yan@gess.uni-mannheim.de)

Funding by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) through CRC TR 224 is gratefully acknowledged.

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

Yihan Yan *

Please click here for the most recent version.

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 one billion less in profit.

*Center for Doctoral Studies in Economics, University of Mannheim, Germany (email: yihan.yan@gess.uni-mannheim.de). I am deeply grateful to my advisors Michelle Sovinsky, Laura Grigolon, Emanuele Tarantino for their guidance and support. I thank Bernhard Ganglmair, Ariel Pakes, John Rust, Bertel Schjerning, Ulrich Wagner and Joel Waldfogel for their invaluable insights. I also thank Alessandra Allocca, Robert Aue, Cristina Bélles-Obrero, Franco Esteban Cattaneo, Ekaterina Kazakova, Harim Kim, Yasemin Özdemir and Eleftheria Triviza for their helpful suggestions. I benefited from the discussions with the attendants to the Bonn-Mannheim Ph.D. Workshop (Bonn), XXIX School in Economic Theory (Jerusalem), 2019 Econometric Society Summer School in Dynamic Structural Econometrics (Chicago), ENTER Jamboree (Tilburg), MACCI IO day (Mannheim), and CRC workshop for young researchers 2019 (Mainz). Funding by the German Research Foundation (DFG) through CRC TR 224 (Project B02) is gratefully acknowledged.

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 (Harhoff et al., 2003). 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 Ericson and Pakes (1995), 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

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

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

with conventional counterpartners. 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 Bajari et al. (2007)) 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 (Lerner and Tirole, 2002; Hann et al., 2004; Raymond, 2001) or incentive of firms to provide open source software (Baake and Wichmann, 2003; Bonaccorsi and Rossi, 2003; Conti et al., 2013; Lerner and Tirole, 2005)[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 (Beresteanu and Li, 2011; Chen et al., 2010; Gallagher and Muehlegger, 2011; Kahn, 2007), or the network effect of charging stations (Li et al., 2017). Beresteanu and Li (2011) and Gallagher and Muehlegger (2011) 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. Li et al. (2017) 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

[3] I follow the classical discrete-choice literature (Berry, 1994; Berry et al., 1995; Nevo, 2001).

[4] The two-step estimation is introduced by Hotz and Miller (1993) into the single-agent dynamic model and extended by Aguirregabiria et al. (2007); Bajari et al. (2007) into dynamic games.

[5] Hann et al. (2004) find that programmers use the contribution to open source software as a signal for productivity. Lerner and Tirole (2005) 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.

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 dynamics. Deviating from Collard-Wexler (2013), Kalouptsidi (2014) and Ryan (2012) 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 -\$218.9 billion to -\$350.8 billion. 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 manufacturers[6] 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 2016[7]. 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%, respectively[8], 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 (Li et al., 2017), 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

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

[7]Jeff 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/

[8]Jeff 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

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 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 rare[9]. 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-scrapping, 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

[9]Steve 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/

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 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.

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

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

Plug-in Hybrid	2012	2013	2014	2015	2016	2017
Price	36.1	35.8	34.9	35.7	37.1	35.4
	(3.43)	(4.07)	(10.3)	(11.9)	(13.0)	(13.5)
Horsepower/Weight	0.41	0.43	0.46	0.47	0.50	0.50
	(0.031)	(0.049)	(0.093)	(0.09)	(0.10)	(0.13)
Miles Per Gallon	4.29	4.21	4.15	3.92	3.91	4.14
	(0.53)	(0.49)	(0.56)	(0.54)	(0.79)	(0.98)
Range on Highway	4.43	4.68	4.84	4.76	4.86	5.11
	(0.79)	(0.83)	(0.83)	(0.83)	(0.82)	(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	41.0	39.6	44.3	50.2	48.6
	(8.74)	(14.6)	(16.6)	(17.5)	(18.6)	(17.3)
Horsepower/Weight	0.41	0.53	0.48	0.55	0.54	0.55
	(0.20)	(0.23)	(0.21)	(0.22)	(0.14)	(0.13)
MPG/MPGe	9.87	10.5	10.9	10.8	10.4	10.5
	(0.48)	(1.08)	(1.07)	(1.16)	(1.16)	(1.20)
Range on Highway	1.09	1.01	1.21	1.37	1.57	1.77
	(0.75)	(0.31)	(0.54)	(0.57)	(0.58)	(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.

Table 3 gives a comparison among PHVs and among EVs before and after open source. 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		Entrants	Incumbents		Entrants
	Before OS	After OS	After OS	Before OS	After OS	After OS
	average (sales-weighted) characteristics					
Price	35.23	32.33	45.11	40.19	45.61	52.72
	(5.91)	(6.99)	(18.20)	(14.68)	(17.48)	(19.12)
Size	1.26	1.32	1.47	1.28	1.28	1.41
	(0.06)	(0.08)	(0.15)	(0.20)	(0.23)	(0.22)
Horsepower/weight	0.43	0.46	0.56	0.49	0.55	0.52
	(0.05)	(0.06)	(0.15)	(0.22)	(0.18)	(0.12)
Range on highway	4.66	4.83	5.13	1.07	1.45	1.76
	(0.82)	(0.78)	(1.09)	(0.48)	(0.58)	(0.55)
MPG/MPGe	4.24	4.16	3.60	10.51	10.68	10.32
	(0.53)	(0.38)	(1.21)	(1.03)	(1.16)	(1.18)
Performance and design	4.1	3.16	3.7	3.6	3.27	4.1
	(0.82)	(0.65)	(0.65)	(0.52)	(0.95)	(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 Ericson and Pakes (1995). 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 (Berry, 1994), 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:

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

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 (Berry et al., 1995; Petrin, 2002; Beresteanu and Li, 2011). 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 Fan (2013), I define each car's absolute quality as

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

In this way, I simplify the cars' heterogeneity from several dimensions to only one. I further follow Goettler and Gordon (2011) 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

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

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

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

where J_f is the set of cars that manufacturer f provides, $\boldsymbol{p}$ is the vector of prices, $\boldsymbol{q}$ is the vector of qualities, $\boldsymbol{\omega}$ is the vector of quality levels, $s_j(\boldsymbol{p}, \boldsymbol{q})$ 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

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

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 υ_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

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

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

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

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

$$C(\omega_j) = \bar{c}\,\omega_i^2 \tag{8}$$

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:

$$\begin{aligned}
&p(\tau_j^t = 2 | x_j^t = 1) = p_2 + \lambda_2 \mathbb{1}(OS_j = 1), \\
&p(\tau_j^t = 1 | x_j^t = 1) = p_1 + \lambda_1 \mathbb{1}(OS_j = 1), \\
&p(\tau_j^t = 0 | x_j^t = 1) = 1 - p(\tau_j^t = 1 | x_j^t = 1) - p(\tau_j^t = 2 | x_j^t = 1),
\end{aligned} \tag{9}$$

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:

$$\omega_j^{t+1} = \omega_j^t + \tau_j^t \mathbb{1}(x_j^t = 1) - \mathbb{1}(x_j^t = 0). \tag{10}$$

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 arrive[11]. 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

$$\chi_j^t(\boldsymbol{\omega}^t, \phi_j^{(e)t}) \in \{0, 1\}, \tag{11}$$

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

$$\xi_j^{(e)t}(\boldsymbol{\omega}^t) \equiv prob(\chi_j^t(\boldsymbol{\omega}^t, \phi_j^{(e)t}) = 1) = \int \chi_j^t(\boldsymbol{\omega}^t, \phi_j^{(e)t}) dF^e(\phi_j^e) \tag{12}$$

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

[11] The 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:

$$V_j^t(\boldsymbol{\omega}^t, \phi_j^t) = \max_{x_j^t \in \{0,1\}} \Big\{ \tilde{\pi}_j^t(\boldsymbol{\omega^t}) + C(\omega_j)x_j^t + \phi_j^t(x_j^t) + \beta E\{V_j^{t+1}(\boldsymbol{\omega}^{t+1}, \phi_j^{t+1}) | \boldsymbol{\omega}^t, \omega_j^{t+1} \neq 0, x_j^t(\boldsymbol{\omega}^t), x_{-j}^t(\boldsymbol{\omega}^t), \xi_{-j}^t(\boldsymbol{\omega}^t)\} \Big\} \tag{13}$$

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:

$$V_j^{(e)t}(\boldsymbol{\omega}^t, \phi_j^{(e)t}) = \max_{\chi_j^{(e)t} \in \{0,1\}} \Big\{ \chi_j^{(e)t} \Big(-\phi_j^{(e)t} + \beta E\{V_j^{(e)t+1}(\boldsymbol{\omega}^{t+1}, \phi_j^{(e)t+1}) | \boldsymbol{\omega}^t, \omega_j^{t+1} \neq 0, \xi_{-j}^{(e)t}(\boldsymbol{\omega}^t), x_{-j}^{(e)t}(\boldsymbol{\omega}^t)\} \Big) \Big\} \tag{14}$$

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 (Ericson and Pakes, 1995; Maskin and Tirole, 1988).

Let σ_j denote the strategy used by PHEV j, which represents entry decisions of potential entrants and investment decisions of incumbents. MPNE requires that each PHEV's strategy is optimal given the strategies of its competitors:

$$V_j(\boldsymbol{\omega}, \phi_j; \sigma_j, \sigma_{-j}) \geq V_j(\boldsymbol{\omega}, \phi_j; \sigma', \sigma_{-j}), \tag{15}$$

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 (Doraszelski and Satterthwaite, 2010).

4 Estimation

Following Bajari et al. (2007), 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 15). 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

$$ln(s_{jt}) - ln(s_{0t}) = \sum_{h=1}^{H} \alpha_h z_{hjt} - \alpha_0 p_{jt} + \eta_{jt}, \tag{16}$$

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 well[12].

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 Berry et al. (1995). 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

$$\Delta_{jk} = \begin{cases} \frac{-\partial s_k}{\partial p_j}, & \text{if } k \text{ and } j \text{ are produced by the same manufacturer;} \\ 0, & \text{otherwise.} \end{cases} \tag{17}$$

Solving for the first-order conditions gives:

$$c_j = p_j - \Delta(\boldsymbol{p}, \boldsymbol{\omega})^{-1} s(\boldsymbol{p}, \boldsymbol{\omega}) \tag{18}$$

[12] I 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:

$$\begin{aligned} c_j(\boldsymbol{\omega}) &= p_j - \Delta(\boldsymbol{p}, \boldsymbol{\omega})^{-1} s(\boldsymbol{p}, \boldsymbol{\omega}) \\ &= \gamma_0 \omega_j + \gamma_1 (\sum_{j=1}^{N} \mathbb{1}(PHEV_j = 1)) + \upsilon_j \end{aligned} \tag{19}$$

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 υ_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 Bajari et al. (2007) 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

$$V(\sigma,\theta)=E\left[\sum_{t=0}^{\infty}\beta^t(\tilde{\pi}_j^t(\boldsymbol{\omega^t})-C(\omega_j)x_j^t(\boldsymbol{\omega^t})+\phi^t(x_j^t))|\omega^0\right], \tag{20}$$

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, $C(\omega_j)=\bar{c}\omega_i^2$ 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 Bajari et al. (2007) by rewriting the value function as the inner product of two vectors and get

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

where $\theta=[1\ \bar{c}\ 1]$. 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 $V(\sigma',\theta)=\left[\tilde{W}^1\ \ \tilde{W}^2\ \ \tilde{W}^3\right]\cdot\theta$, 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***	-0.136***	-0.135***	-0.134***	-0.133***
	(0.0120)	(0.0121)	(0.0119)	(0.0122)	(0.0120)
Size (L*W)	5.128***	5.208***	5.142***	4.797***	4.742***
	(0.475)	(0.480)	(0.473)	(0.552)	(0.546)
Horsepower/Weight	1.286***	1.337***	1.303***	1.201***	1.174***
	(0.351)	(0.355)	(0.351)	(0.365)	(0.361)
MPG/MPGe	0.0973***	0.0929***	0.0949***	-0.0167	-0.0162
	(0.0350)	(0.0352)	(0.0351)	(0.0630)	(0.0628)
Cargo Volume	0.251***	0.252***	0.250***	0.238***	0.237***
	(0.0353)	(0.0357)	(0.0354)	(0.0357)	(0.0354)
Navigation	1.068***	1.091***	1.068***	1.055***	1.038***
	(0.170)	(0.173)	(0.170)	(0.174)	(0.171)
Range on Highway	0.194***	0.187***	0.191***	0.249***	0.253***
	(0.0416)	(0.0416)	(0.0414)	(0.0543)	(0.0539)
Overall Performance and Design	0.196***	0.197***	0.195***	0.200***	0.199***
	(0.0265)	(0.0267)	(0.0265)	(0.0265)	(0.0264)
PHEV	-1.560***	-1.530***	-1.553***		
	(0.250)	(0.252)	(0.250)		
time trend (quarter)		-0.0126**		-0.0123**	
		(0.00582)		(0.00573)	
time trend (year)			-0.0496**		-0.0480**
			(0.0228)		(0.0225)
PHV				-1.474***	-1.492***
				(0.253)	(0.251)
EV				-0.424	-0.433
				(0.588)	(0.587)
Constant	-14.42***	-14.45***	-14.40***	-13.92***	-13.88***
	(0.473)	(0.475)	(0.470)	(0.578)	(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 three[13].

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

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

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

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

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

Table 8: Marginal Cost

	(1)	(2)	(3)	(4)
	OLS		IV	
Quality	6.069***	5.966***	4.547***	4.706***
	(0.367)	(0.365)	(0.578)	(0.518)
No. PHEV Model		-0.125***		-0.158***
		(0.0420)		(0.0288)
Constant	13.02***	17.18***	16.99***	21.32***
	(2.572)	(2.905)	(1.826)	(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 after[14]. 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

[14]For 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

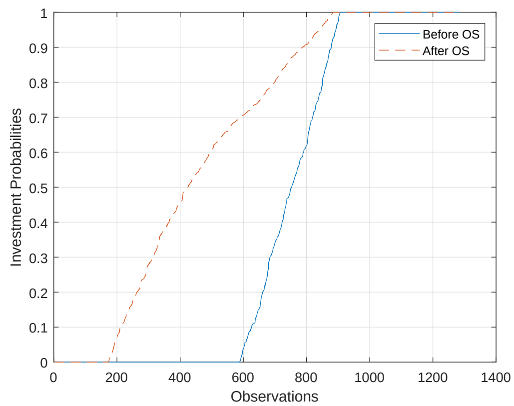
The standard deviations are conducted by bootstrapping.

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.

[15] Edward 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.

[16] Matthew 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.

[17] Steve 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/.

[18] Esha 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**	**1500**
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**

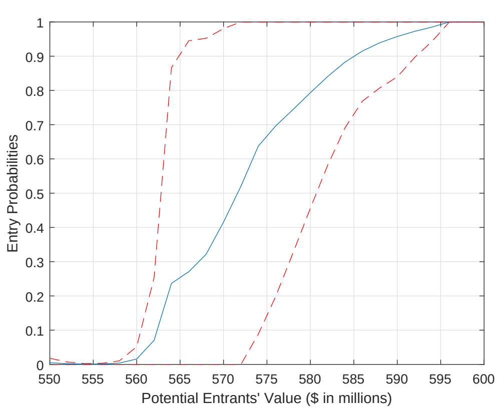


Figure 2: Before Open Source

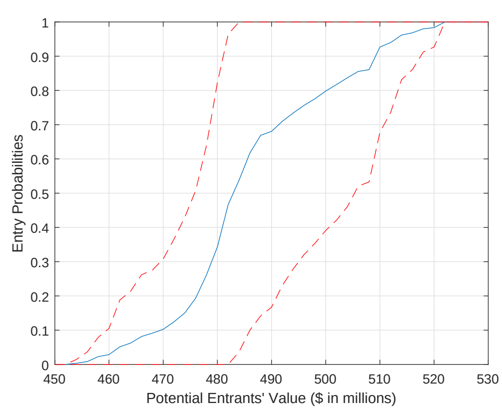


Figure 3: After Open Source

6 Counterfactual simulation

Several questions remain unanswered so far: what is the incentive of Tesla being open source, when there seems to be no direct benefit? How would the industry develop if there is no open source? How to compare the benefit from the lower investment cost and from the decreased entry cost?

One main appeal of the structural model is that I can experiment with the different scenarios using simulation analysis. To understand why Tesla chose to open source and how the PHEV industry would have evolved without the open source initiative, I conduct a simulation of the industry dynamics, shutting down the benefit that open source brings. After the third quarter of 2014, at which point the open source initiative in reality occurs, I force the players in the market to face the higher entry costs and unit investment cost as estimated prior to the open source event. As discussed in the model section, players choose optimal strategies based on the industry structure, own quality, investment cost or entry cost, and the randomly drawn private cost shock. This assumption allows me to use the estimated policy functions based on the observed behaviors of all PHEVs before open source occurs. I then use these policy functions to predict how the players respond in terms of investment choice and entry decisions, and the evolution of the industry in the simulated case.[19]

At the beginning of my simulation, which is the third quarter of 2014, I observe eighteen PHEVs being active in the market. These 18 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. They made up the total sales of 34,335 units in that quarter, which only account for 1% of the whole car market.

The simulation unfolds the events as described in section 3. Five potential entrants arrive at the beginning of the period, with both quality levels and brands randomly drawn. Based on the current industry structure, i.e., the quality distribution of incumbents, and their own quality levels, the policy function of entry predicts whether some potential entrants will enter. Simultaneously, I randomly draw an exit shock, which will determine whether one of the incumbents with the lowest-quality will leave the market. Then, ran-

[19]The simulation case is a simple forward play of what I observe in reality in the PHEV industry before open source. That means the players form the expectation and make decisions in the same way as I estimated prior to open source. That gives me the opportunity to circumvent solving a computational demanding equilibrium in the simulation. However, to evaluate other policies in such a setting, one need to solve for the equilibrium. I will leave this to future research.

dom draws on investment cost shocks and the investment policy function determine each remaining PHEV incumbent, whether it will invest or not. The incumbents, excluding the new entrants and the one that exits the market, compete in the product market together with the conventional counterpartners. I back out the marginal production cost of each car based on equation (5), given their quality levels and brands, and calculate the market share of PHEVs and conventional cars using the estimated taste parameters and price sensitivity. Then, I am able to compute the product market profits of all PHEV players. Together with the unit investment cost and their investment decisions, I obtain the per-period payoff as discussed by equation (4). At the end of the period, I draw the realization of the investment outcomes according to the estimation of the equation (9) and each PHEV evolves as (10) describes. The industry structure for the next period is then determined by the evolution of the incumbents, the entry decisons of the entrants and the exit event.

I forward simulate the PHEV industry development until the last quarter of 2017, which is the last period that my data captures. I repeat this whole process for 500 times to compute the average simulated industry structure. Using the simulated per-period payoffs and the discount factor, I can conduct the discounted value for all PHEVs and conventional cars from the third quarter of 2014 to the last quarter of 2017.

6.1 Tesla's Profit

To understand why Tesla use open source, I compute the discounted return of Tesla in the simulated scenario,

$$\begin{aligned} V_{Tesla}^{2014Q3-2017Q4} = \sum_{t=2014Q3}^{2017Q4} \sum_{j \in Tesla} \beta^t \Big(& \mathbb{1}(j \in incumbent)(\tilde{\pi}_j^t(\hat{\boldsymbol{\omega}}^{\boldsymbol{t}}) + C(\hat{\omega}_j)\hat{x}_j^t + \phi_j^t(\hat{x}_j^t)) \\ & + \mathbb{1}(j \in entrant)\hat{\chi}_j^{(e)t}(-\phi_j^{(e)t}), \Big) \end{aligned} \tag{21}$$

which is the sum of the discounted return of all PHEVs that belongs to Tesla, that could be both incumbents or entrants. The terms $\hat{\boldsymbol{\omega}}$ and $\hat{\omega}_j$ are the simulated industry structure and the simulated quality structure of Tesla's car, $C(\cdot)$ represent the estimated investment cost function prior to the open source event, $\hat{x}_j^t$ and $\hat{\chi}_j^{(e)t}$ indicate the simulated investment and entry choices, ϕ_j^t and $\phi_j^{(e)t}$ are the individual private cost shocks regarding investment behavior or entry decision.

I make the same analysis for Tesla using the real data, i.e., I replace the simulated industry structure and simulated decisions by the observed structure and behaviors in the equation (21). The data from the third quarter of 2014 to the last quarter of 2017 shows that Tesla has in total three car models being active in this period, with the names "Model S", "Model X" and "Model 3". Model S is already in the market in the interested periods, while Model X enters in the third quarter of 2015 and Model 3 in the third quarter of 2017. The quality level of Model S and Model X are both on average above five, while Model 3 is on level one. They make investments in 90% of the time compared to the probability of 83% from the rest of the industry.

Table 12 shows the result of the above-described analysis. The first column documents the calculation based on the data, and column two shows the results from the counterfactual analysis. As those discounted values are conducted from 500 simulations, I also report the standard deviation in the parenthesis. The first row suggests that Tesla has a negative sum of discounted pre-period return (-$3.51 billion), if the industry would have evolved without open source and PHEVs face higher investment and entry costs. Whereas Tesla still has negative but a bit higher discounted return of -$ 2.19 billion for the same time period if open source occurs.

I then separate the total discounted returns into the sum of the discounted investment expenditure, the sum of the discounted per-period market profit, and the sum of discounted entry expenditure to explore on which part open source has the most significant effect. The results are reported in the second to fourth rows in Table 12. It shows that investment expenditure accounts for most of the discounted return. Due to the higher unit investment cost without the open source initiative, the simulated case's investment expenditure is substantially higher than in the case that I observed in the data. However, the profit and entry cost is lower in the counterfactual scenario, which seems counterintuitive. This is due to the fact that Tesla has less incentive to introduce new cars in the market, when facing the high entry costs in the simulated case. Whereas I observe two Tesla cars enter the market during the third quarter of 2014 to the end of 2017 in the data, on average only in 40% of the simulations Tesla introduces one new car and 17% of the times more than one new model. With fewer cars in the market, Tesla collects naturally less profit.

Table 12: Tesla: Comparison of Data with Simulation (2014Q3-2017Q4)

	With OS (Data)	Without OS (1.Simulation)	Without OS (2.Simulation)
Discounted Return (10M$)	-218.9	-350.8	-432.1
		(111.5)	(110.7)
Investment Expenditure (10M$)	-215.5	-326.1	-401.2
		(119.8)	(118.7)
Profit(10M$)	47.5	23.7	35.9
		(9.8)	(9.4)
Entry Cost(10M$)	-50.9	-21.5	-70.4
		(13.3)	(31.0)

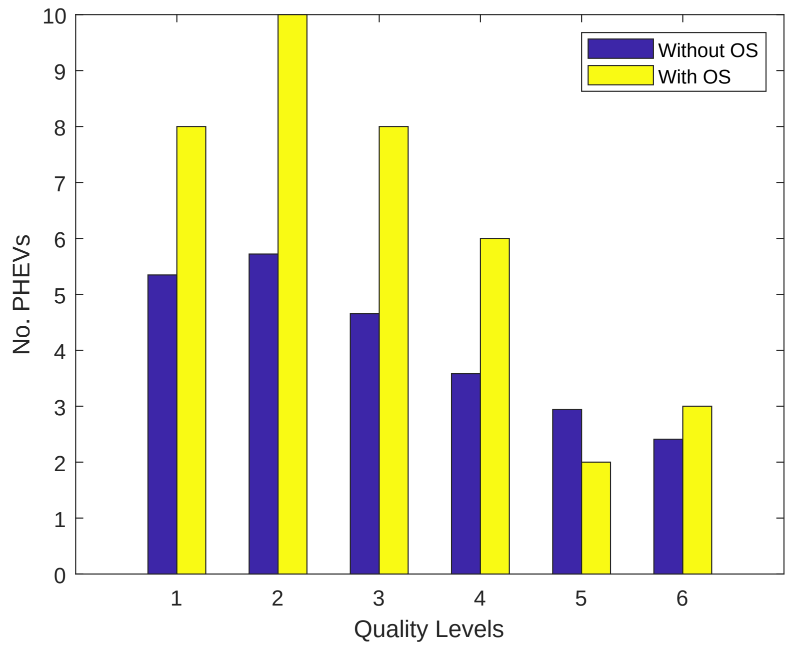
Standard errors in parentheses

To better understand the trade-off of the entry costs and the competition levels in the product market, I run another set of simulations. On top of the setting described previously, I also force Tesla to introduce two new cars into the market. The timing of the introduction and the quality levels of these two cars is assumed to be the same as in the data. The last column in Table 12 shows the results of this simulation. In this case, the discounted return of Tesla is even lower than the first simulation. That is intuitive, as I deliberately let Tesla to deviate from the optimal entry strategy in this analysis. The investment expenditure and entry costs are both higher in this scenario, as Tesla has more cars in this counterfactual case. The profit is higher than in the first simulation, as there are more Tesla cars in the product market, but still lower than the one from the data, which is a result of low incentive to invest. Due to the high unit investment cost, Tesla is less likely to invest in the simulated case and ends up with lower quality levels. The average investment probability across all Tesla cars is 0.87 in the simulation, with an average quality level of 3.68, while these numbers are 0.90 and 5.30 in the data.

6.2 Industry Structure

Using the same simulation process, I explore how the whole PHEV industry structure evolves in this subsection. To visualize the effect of open source on the expansion of the PHEV industry, I report the quality distribution of PHEVs in the market in the last quarter of 2017 in Figure 4.

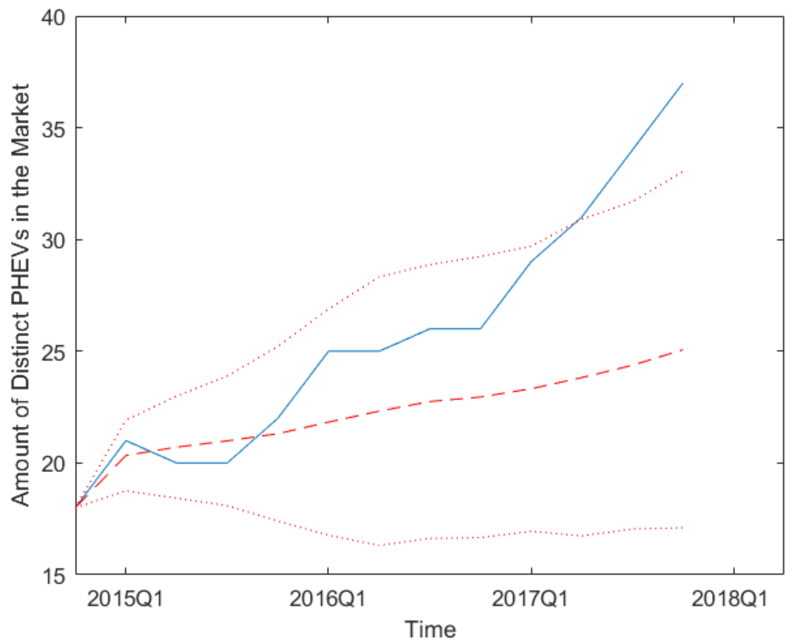
Figure 4: Quality Level Distribution of PHEVs in 2017 Q4



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 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.

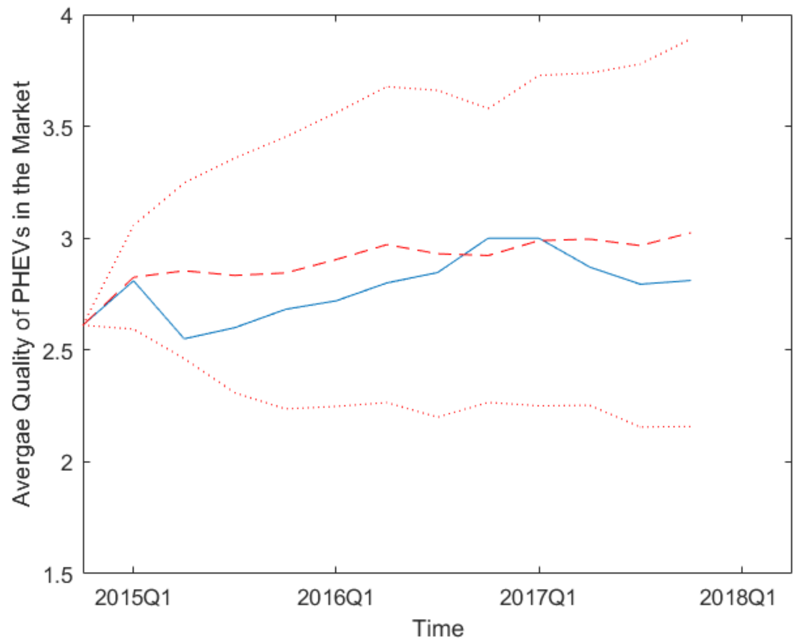
Figure 5 shows the industry dynamics from the third quarter of 2014 until the last quarter of 2017. The horizontal axis represents the time while the vertical axis displays the number of distinct PHEV models in each quarter. The blue solid line shows the industry structure based on data, and the red dashed line represents the structure in the simulated scenario. The red dotted line shows the 95% confidence interval of the simulated number of PHEVs. In both cases, I observe a clear expansion of the market, while in the real data, the expansion speed is significantly faster than in the simulated case, which is due to the high entry costs in the simulation.

Figure 5: Number of PHEVs in Data and in Counterfactual 2014Q3 – 2017Q4



I show the quality dynamics in Figure 6, where I report the average quality level in each quarter. The blue solid line captures the overall quality changes in the data after open source occurs, where we see a clear trend of improvement. The red dashed line represents the average quality levels in the simulated case, where I force the industry to evolve as if there is no open source. The red dotted lines are the 95% confidence interval. I also see a slight improvement trend in the counterfactual scenario. Surprisingly, the average simulated quality is almost always higher than the one documented by the data. The explanation is that there are relatively few entrants in the simulated case, especially those in the low-quality levels (as shown in Figure 4). Thus, not only is the quality dispersion higher in the data, but more low-quality cars also enter and drag down the overall quality levels.

Figure 6: Quality of PHEVs 2014Q3 – 2017Q4



I then compute the total amount of discounted return for all PHEV, their investment expenditures, profits from the product market and entry expenditure. The comparison between the data and the simulation is shown in the first panel of Table 13. The discounted return in the simulated case is lower than in the data, as the investment expenditure is substantially higher. The total profit is higher in the data. However, recall there are only on average 25 distinct car models in the simulation, opposed to 37 models in the reality. That suggests the average discounted profit is actually higher in the simulation, as a result of the milder competition in the product market.

I further break down the cars into two categories: incumbents and entrants. I define a PHEV model as incumbent if it is already in the market in the third quarter of 2014. All cars that enter the market later than that time point are defined as entrants. The incumbents' investment expenditure in the period of 2014Q3 to 2017Q4 is lower in the simulated case than in the data, while the profits are quite similar. As the incumbent PHEVs are less likely to invest in the simulated scenario, their average quality levels are also slightly lower than what I observe in reality. Thus, they lose some profits in the product market. However, the incumbents are at the same time better off, as they face

Table 13: All PHEVs: Comparison of Data with Simulation (2014Q3-2017Q4)

	Data		Simulation	
Discounted Return (B$)	-12.83		-13.24	
			(3.56)	
Investment Expenditure (B$)	-10.25		-14.32	
			-2.23	
Profit(B$)	3.36		2.66	
			(2.17)	
Entry Cost(B$)	-5.94		-1.58	
			(1.70)	
	Incumbent	Entrant	Incumbent	Entrant
No. Model	18	19	18	6.32
Discounted Return (B$)	-3.23	-9.9	-9.48	-3.76
			(3.75)	(1.41)
Investment Expenditure (B$)	-5.58	-4.67	-11.6	-2.72
			(4.04)	(1.21)
Profit (B$)	2.35	0.71	2.12	0.54
			(1.32)	(0.29)
Entry Cost(B$)	0	-5.94	0	-1.58
			-	(1.70)
Prob. of Investment	0.85	0.81	0.82	0.80
			(0.04)	(0.11)
quality levels	2.56	3.08	2.47	3.43
			(0.22)	(0.62)

Standard errors in parentheses

fewer competitors due to the fact that fewer potential entrants find it profitable to enter the market. These two opposite effects result in comparable profits in the end.

On average, 6 new PHEVs enter the market in the simulated case, whereas I observe 19 new models in the data. This explains why all the entrants' values are smaller in the absolute term in the simulation than in the data, as they are the sum of all the entrants. It is worth noting that the average quality levels are higher in the simulation, suggesting that high entry costs deter low-quality cars. That, together with the milder competition in the product market, explains the entrant's disproportional high profits in the counterfactual case, even though the amount of the entrant PHEV is only one-third of what is observed in the data.

Other than the statistics I present in Table 13, I also compute the total market share of PHEVs for the interested period in the simulated scenario. Recall that the market is defined as the US households that do not make any purchase of cars in the previous year. In the data, the total market share of PHEVs is 0.0019 in the last quarter of 2017, while in the counterfactual analysis, this number is 0.0009. That shows the negative effect on the market share from the high entry cost outweighs the positive effect from the milder competition.

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 discount return turns out to be -3.5 billion dollars, which is more than one billion less then what I calculated based on the 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.

From a policy perspective, it is reasonable to encourage the leading firms in a newly emerging industry to engage in sharing their advanced technology. It will not only lead to an expansion of the interested sector, but the open source firm may also have monetary returns from such behavior. If open source is not a feasible alternative, it is recommended to provide subsidy on innovation, as the counterfactual analysis suggests that a reduction in the investment costs is essential for a better development of the industry.

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.

References

Victor Aguirregabiria, Pedro Mira, and Hernan Roman. An estimable dynamic model of entry, exit, and growth in oligopoly retail markets. *The American economic review*, 97 (2):449–454, 2007.

Pio Baake and Thorsten Wichmann. Open source software, competition and potential entry. *Journal of Economic Literature*, 2003.

Patrick Bajari, C Lanier Benkard, and Jonathan Levin. Estimating dynamic models of imperfect competition. *Econometrica*, 75(5):1331–1370, 2007.

Arie Beresteanu and Shanjun Li. Gasoline prices, government support, and the demand for hybrid vehicles in the united states. *International Economic Review*, 52(1):161–182, 2011.

Steven Berry, James Levinsohn, and Ariel Pakes. Automobile prices in market equilibrium. *Econometrica: Journal of the Econometric Society*, pages 841–890, 1995.

Steven T Berry. Estimating discrete-choice models of product differentiation. *The RAND Journal of Economics*, pages 242–262, 1994.

Andrea Bonaccorsi and Cristina Rossi. Why open source software can succeed. *Research policy*, 32(7):1243–1258, 2003.

Jiawei Chen, Susanna Esteban, and Matthew Shum. Do sales tax credits stimulate the automobile market? *International Journal of Industrial Organization*, 28(4):397–402, 2010.

Allan Collard-Wexler. Demand fluctuations in the ready-mix concrete industry. *Econometrica*, 81(3):1003–1037, 2013.

Annamaria Conti, Jerry Thursby, and Marie Thursby. Patents as signals for startup financing. *The Journal of Industrial Economics*, 61(3):592–622, 2013.

Ulrich Doraszelski and Mark Satterthwaite. Computable markov-perfect industry dynamics. *The RAND Journal of Economics*, 41(2):215–243, 2010.

Richard Ericson and Ariel Pakes. Markov-perfect industry dynamics: A framework for empirical work. *The Review of Economic Studies*, 62(1):53–82, 1995.

Ying Fan. Ownership consolidation and product characteristics: A study of the us daily newspaper market. *The American Economic Review*, 103(5):1598–1628, 2013.

Kelly Sims Gallagher and Erich Muehlegger. Giving green to get green? incentives and consumer adoption of hybrid vehicle technology. *Journal of Environmental Economics and management*, 61(1):1–15, 2011.

Ronald L Goettler and Brett R Gordon. Does amd spur intel to innovate more? *Journal of Political Economy*, 119(6):1141–1200, 2011.

Il-Horn Hann, Jeff Roberts, Sandra Slaughter, and Roy Fielding. An empirical analysis of economic returns to open source participation. *Unpublished working paper, Carnegie-Mellon University*, 2004.

Dietmar Harhoff, Joachim Henkel, and Eric Von Hippel. Profiting from voluntary information spillovers: how users benefit by freely revealing their innovations. *Research policy*, 32(10):1753–1769, 2003.

V Joseph Hotz and Robert A Miller. Conditional choice probabilities and the estimation of dynamic models. *The Review of Economic Studies*, 60(3):497–529, 1993.

Matthew E Kahn. Do greens drive hummers or hybrids? environmental ideology as a determinant of consumer choice. *Journal of Environmental Economics and Management*, 54(2):129–145, 2007.

Myrto Kalouptsidi. Time to build and fluctuations in bulk shipping. *American Economic Review*, 104(2):564–608, 2014.

Josh Lerner and Jean Tirole. Some simple economics of open source. *The journal of industrial economics*, 50(2):197–234, 2002.

Josh Lerner and Jean Tirole. The economics of technology sharing: Open source and beyond. *The Journal of Economic Perspectives*, 19(2):99–120, 2005.

Shanjun Li, Lang Tong, Jianwei Xing, and Yiyi Zhou. The market for electric vehicles: indirect network effects and policy design. *Journal of the Association of Environmental and Resource Economists*, 4(1):89–133, 2017.

Eric Maskin and Jean Tirole. A theory of dynamic oligopoly, i: Overview and quantity competition with large fixed costs. *Econometrica: Journal of the Econometric Society*, pages 549–569, 1988.

Aviv Nevo. Measuring market power in the ready-to-eat cereal industry. *Econometrica*, 69 (2):307–342, 2001.

Amil Petrin. Quantifying the benefits of new products: The case of the minivan. *Journal of political Economy*, 110(4):705–729, 2002.

Eric S Raymond. The cathedral and the bazaar-musings on linux and open source by an accidental revoltionary (rev. ed.)., 2001.

Stephen P Ryan. The costs of environmental regulation in a concentrated industry. *Econometrica*, 80(3):1019–1061, 2012.