Essays in Empirical Industrial Organization

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Yihan Yan

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Abteilungssprecher: Prof. Dr. Volker Nocke
Referent: Prof. Michelle Sovinsky, Ph.D.
Korreferent: Prof. Laura Grigolon, Ph.D.

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Gerneral Introduction

This dissertation consists of three self-contained chapters. The underlying themes are the analysis of firms' strategic behavior under a dynamic framework, when facing changes in the competitive environment due to certain firm's behavior, economic shocks, or policy regulations in the market.

The first two chapters investigate how technology sharing promotes the development of a newly emerging market – plug-in hybrid and electric vehicle industry in the US. In chapter one, I explore the effects of open source initiative on car manufacturers' entry decisions and quality positionings. Chapter two explains why it is profitable for firms to share their technologies and how the whole industry benefits from it. The third chapter is co-authored with Michelle Sovinsky, where we analyze whether advertising can be used as a pre-emptive tool.

In what follows, I summarize each chapter.

Chapter 1
Does Open Source Pay off in the Plug-in Hybrid and Electric Vehicle Industry? A Study of Tesla's Open-Source Initiative

In this chapter, I quantify the effect of Tesla's open source initiative on the development of the plug-in hybrid and electric vehicle (PHEV) industry in the US. On the one hand, open source allows the PHEV manufacturers to use the more advanced technology of Tesla, which leads to a lower investment cost and a higher incentive to invest. Open source also provides more information for the potential PHEV producers, which may partially remove the entry barriers. This attracts more entrants and induces economies of scale to decrease manufacturing costs. On the other hand, underinvestment of Tesla's rivals may occur as a result of free riding, which could lead to slower quality improvement in the industry.

To capture the various impacts of open source, I develop and estimate a dynamic structural oligopoly model, where I incorporate entry and investment decisions of each PHEV and allow marginal manufacturing costs to depend on the number of active PHEVs. Using the two-step estimation technique, I recover the investment cost and distribution of entry costs before and after open source which took place in June 2014. My results show that open source results in a 60% drop in investment costs, and a decrease of approximately 100 million in entry costs into the PHEV industry.

Chapter 2
Valuation of Open Source – Evidence from the US Automobile Industry

In this chapter, I use the framework and estimation proposed and employed in the previous chapter to conduct a counterfactual analysis, where the open source movement does not take place. The aim is to evaluate how the reduction in investment cost and entry cost induced by open source affect the industry structure and the monetary returns of the PHEV manufacturers.

More precisely, I forward simulate the PHEVs strategic behavior of entry and investment under the assumption that the entry cost distribution and unit investment cost are as high as before open source occurred. In addition, I perform a reduced-form analysis using the estimates from the previous chapter to distinguish the effect of these two costs on the market expansion.

I find that fewer PHEVs are present in the simulated scenario. While there are 37 distinct models in the data, only 25 PHEVs exist in the counterfactual analysis. The overall discounted returns of PHEVs are lower as well, mainly driven by the substantially high investment expenditure. Compared to the reduction of entry costs, the decrease in investment cost explains the market expansion more.

Chapter 3
The Pre-emptive Effects of Advertising: Dynamics in the CPU Industry

This chapter is joint work with Michelle Sovinsky. We investigate the role of advertising in the CPU industry, taking into account the dynamic nature of advertising. That is, the advertisement today will have an impact on consumers' purchase decisions tomorrow. In particular, we test whether Intel uses advertising as a preemptive tool to weaken its main rival – AMD.

We find, in general, both CPU manufacturers enjoy a positive return to their revenue from advertisement expenditure, and advertising is not only effective in the current period but also for the future. However, during the period when Intel is accused of illegally using the marketing campaign, an Intel CPU with better quality and higher advertisement expenditure does not necessarily lead to a higher profit. That suggests Intel indeed use advertising in an anti-competitive fashion.

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

1.1 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

[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

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 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]

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

[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.

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 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.

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 conclude in section 6.

1.2 Industry and Data

1.2.1 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 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

[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

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.

1.2.2 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 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

[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/

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 1.1 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 1.1, 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.

[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 1.1: 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 1.2 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 1.3 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

Table 1.2: 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.

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.

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.

Table 1.3: 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	

1.3 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.

1.3.1 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:

$$u_{ij} = \sum_{h=1}^{H} \alpha_h z_{hj} - \alpha_0 p_j + \eta_j + \epsilon_{ij}, \tag{1.1}$$

where z_{hj} represents the h-th car observable characteristics (discussed in section 1.2.2), 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

$$q_j = \sum_{h=1}^{H} \alpha_h z_{hj} + \eta_j. \tag{1.2}$$

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 1.5.1.

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

$$s_j = \frac{exp(q_j - \alpha_0 p_j)}{1 + \sum_{\omega_k \neq 0} exp(q_k - \alpha_0 p_k)}. \tag{1.3}$$

1.3.2 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

$$\pi_f(\boldsymbol{p}, \boldsymbol{q}, \boldsymbol{\omega}) = \sum_{j \in J_f} \pi_j(\boldsymbol{p}, \boldsymbol{q}, \boldsymbol{\omega}) = \sum_{j \in J_f} s_j(\boldsymbol{p}, \boldsymbol{q}) M[p_j - c_j(\boldsymbol{\omega})], \tag{1.4}$$

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 1.4 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

$$c_j(\boldsymbol{\omega}) = \begin{cases} \gamma_0 \omega_j + \upsilon_j & \text{if } j \text{ is conventional car,} \\ \gamma_0 \omega_j + \gamma_1 (\sum_{j=1}^{N} \mathbb{1}(PHEV_j = 1)) + \upsilon_j & \text{if } j \text{ is PHEV.} \end{cases} \tag{1.5}$$

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

$$\frac{\partial \pi_f}{\partial p_j} = M \left(s_j + \sum_{k \in J_f} (p_k - c_k(\boldsymbol{\omega})) \frac{\partial s_k(\boldsymbol{p}, \boldsymbol{q}, \boldsymbol{\omega})}{\partial p_j} \right) = 0 \text{ for all } j \in J_f. \tag{1.6}$$

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

$$\tilde{\pi}_j^t(\boldsymbol{\omega^t}) + C(\omega_j) x_j^t + \phi_j^t(x_j^t), \tag{1.7}$$

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

$$C(\omega_j) = \bar{c}\, \omega_i^2 \tag{1.8}$$

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:

$$p(\tau_j^t = 2 | x_j^t = 1) = p_2 + \lambda_2 \mathbb{1}(OS_j = 1), \tag{1.9}$$
$$p(\tau_j^t = 1 | x_j^t = 1) = p_1 + \lambda_1 \mathbb{1}(OS_j = 1), \tag{1.10}$$
$$p(\tau_j^t = 0 | x_j^t = 1) = 1 - p(\tau_j^t = 1 | x_j^t = 1) - p(\tau_j^t = 2 | x_j^t = 1), \tag{1.11}$$

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:

$$\omega_j^{t+1} = \omega_j^t + \tau_j^t \mathbb{1}(x_j^t = 1) - \mathbb{1}(x_j^t = 0). \tag{1.12}$$

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.

1.3.3 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

$$\chi_j^t(\boldsymbol{\omega}^t, \phi_j^{(e)t}) \in \{0, 1\}, \tag{1.13}$$

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,

[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.

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

$$\xi_j^{(e)t}(\boldsymbol{\omega}^t) \equiv prob(\chi_j^t(\boldsymbol{\omega}^t, \phi_j^{(e)t}) = 1) = \int \chi_j^t(\boldsymbol{\omega}^t, \phi_j^{(e)t}) dF^e(\phi_j^e) \tag{1.14}$$

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

1.3.4 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 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.

1.3.5 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:

$$\begin{aligned} V_j^t(\boldsymbol{\omega}^t, \phi_j^t) = \max_{x_j^t \in \{0,1\}} \Big\{ & \tilde{\pi}_j^t(\boldsymbol{\omega^t}) + C(\omega_j) x_j^t + \phi_j^t(x_j^t) \\ & + \beta E\{V_j^{t+1}(\boldsymbol{\omega}^{t+1}, \phi_j^{t+1}) | \boldsymbol{\omega}^t, \omega_j^{t+1} \neq 0, x_j^t(\boldsymbol{\omega}^t), x_{-j}^t(\boldsymbol{\omega}^t), \xi_{-j}^t(\boldsymbol{\omega}^t)\} \Big\} \end{aligned} \tag{1.15}$$

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:

$$V_j^{(e)t}(\boldsymbol{\omega}^t, \phi_j^{(e)t}) = \max_{\chi_j^{(e)t} \in \{0,1\}} \Big\{ \chi_j^{(e)t} \tag{1.16}$$

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

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:

$$V_j(\boldsymbol{\omega}, \phi_j; \sigma_j, \sigma_{-j}) \geq V_j(\boldsymbol{\omega}, \phi_j; \sigma', \sigma_{-j}), \tag{1.17}$$

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 (Doraszelski and Satterthwaite, 2010).

1.4 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 1.1) and construct the discretized quality level for each car model using those estimates (see equation 1.2), 2) infer marginal costs from the car model's first-order condition for optimal pricing (see equation 1.6), 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 1.9).

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 1.17). 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.

1.4.1 First stage estimation

Consumer demand and quality

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

$$ln(s_{jt}) - ln(s_{0t}) = \sum_{h=1}^{H} \alpha_h z_{hjt} - \alpha_0 p_{jt} + \eta_{jt}, \tag{1.18}$$

where s_j is the market share of the car model j given in equation 1.3 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 1.2. I then discretize them into quality level ω_j.

Marginal cost

Multi-product car manufacturers choose the set of prices to maximize their overall profits as described in equation 1.6. I first define a J by J matrix Δ, where the (j, k) element is given by

$$\Delta_{jk} = \begin{cases} \frac{-\partial s_k}{\partial p_j}, & \text{if } k \text{ and } j \text{ are produced by the same manufacturer;} \\ 0, & \text{otherwise.} \end{cases} \tag{1.19}$$

[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.

Solving for the first-order conditions gives:

$$c_j = p_j - \Delta(\boldsymbol{p}, \boldsymbol{\omega})^{-1} s(\boldsymbol{p}, \boldsymbol{\omega}) \tag{1.20}$$

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

$$\begin{aligned} c_j(\boldsymbol{\omega}) &= p_j - \Delta(\boldsymbol{p}, \boldsymbol{\omega})^{-1} s(\boldsymbol{p}, \boldsymbol{\omega}) \\ &= \gamma_0 \omega_j + \gamma_1 (\sum_{j=1}^{N} \mathbb{1}(PHEV_j = 1)) + \upsilon_j \end{aligned} \tag{1.21}$$

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 υ_j can be potentially correlated with the quality level ω_j, I apply the same set of instruments as discussed in section 1.4.1.

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.

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.

1.4.2 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

$$V(\sigma,\theta) = E\left[\sum_{t=0}^{\infty} \beta^t (\tilde{\pi}_j^t(\boldsymbol{\omega^t}) - C(\omega_j)x_j^t(\boldsymbol{\omega^t}) + \phi^t(x_j^t))|\omega^0\right], \tag{1.22}$$

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

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

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.

1.5 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.

1.5.1 First-stage estimates

Demand estimates

The estimation results of the taste parameters are shown in table 1.4 using the instrument described in section 1.4.1. 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, but also the preference on fuel economy, yielding a biased result. Thus, I should not use the separate dummies.

Table 1.4: 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

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

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

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 1.5 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 1.5: 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 1.6 and 1.7 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 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.

[13]I experimented with different cut-off points.

Table 1.6: 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 1.7: 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)

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 1.8.

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.

Table 1.8: 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
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

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

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

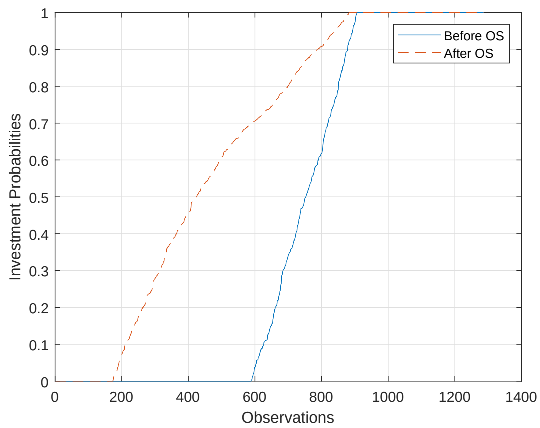
Table 1.9: Transition

	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.

predict investment and entry probability of all possible states. In figure 1.1, 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.

Figure 1.1: Comparison in Investments



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

As shown in table 1.10, 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 1.10: 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 1.11. 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.

[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 1.11: 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**

Figures 1.2 and 1.3 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.

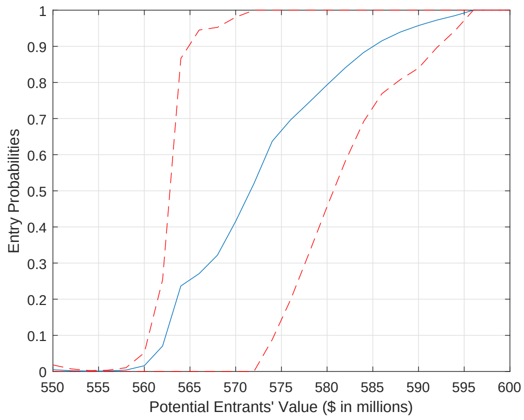


Figure 1.2: Before Open Source

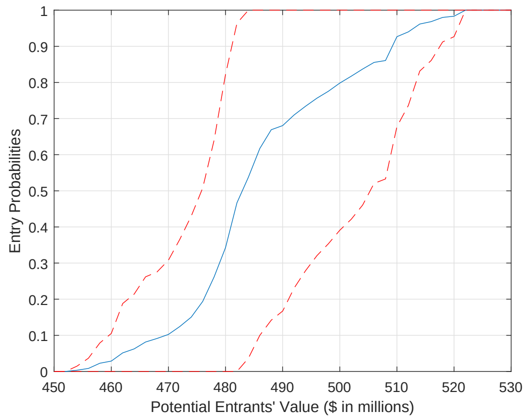


Figure 1.3: After Open Source

1.6 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.

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.

2 Valuation of Open Source – Evidence from the US Automobile Industry

2.1 Introduction

The evaluation of open source is a subject of increasing interest. It is a concept proposed by the software industry and gradually adopted by other sectors. In contract to proprietary software, everyone can use, distribute and modify the source code of an open source software. Extended to other industries, it provides a new approach of innovation and may generate different market pattern, compared to the case where there are only in-house closed source innovations. A better understanding of the advantages and disadvantages that an open source movement could bring to a newly emerging industry is particularly essential for policy-makers.

Previous literature focuses mainly on understanding the impact of open source on the software industry. Papers discussing how programmer benefits from open source includes Raymond (2001), Lerner and Tirole (2002) and Roberts et al. (2006). Raymond (2001) suggests that programmers who participate in developing open source code gain enjoyment from fixing bugs and being recognized as members of a group with intellectual curiosity. Lerner and Tirole (2002) argue that programmers are usually both developers and end-users. As developers, they signal their productivity in the participation of the open source project and as end-user they benefit from the improved quality or desired function of the software. Roberts et al. (2006) find that the clearer feedback system adopted by projects that use open source software is positively related to the programmers' motivation and, hence, their performance.

There is vast literature discussing how the software industry enjoys the benefits brought by open source movement. Bonaccorsi and Rossi (2003) point out that open source accelerates the diffusion of technology in the presence of network externality. Though the software is no longer private goods and can not be the source of revenue, firms can still gain higher profit by selling complement hardware or services to a larger group. Bessen (2005) finds that firms are more likely to engage in open source movement, when facing sophisticated software. And that increases social welfare as less inefficiency occurs in developing such software. Harhoff et al. (2003) provide the idea that an innovation revealed freely and adopted by others can become an informal standard. In this sense, open-source firms often join collaborations in order to develop codes in directions that favor their own technology and gain a permanent advantage. Lerner and Tirole (2005) suggest another benefit of using open source is that making codes available to everyone induces the sophisticated end-users to debug and to improve the quality of the software. That directly decreases the coding cost.

Recent research tried to understand why other industries also started to adopt the open source concept. The bio-pharmaceutical firms employ open source organizational modes to solve complex projects. These projects require the acquisition of diverse ideas and solutions from outsiders, and, thus, an open innovation approach may be better suited to deal with high complexity (Chiaroni et al., 2009; Lee et al., 2019). Lee et al. (2010) suggest that SMEs engaging in open innovation are more likely to form collaboration networks, facilitate their innovation capabilities, and improve their innovation performance. Laursen and Salter (2006) empirically support those arguments using the U.K. innovation survey of manufacturing firms.

In this paper, I analyze how open source contributes to the development of the plug-in hybrid and electric vehicle industry (PHEV) in the US. Using the model and estimates from Yan (2020), I conduct a counterfactual analysis in a world, where Tesla, a leading firm in producing PHEVs, does not share the technology with its competitors. In particular, I am interested in evaluating how the reduction in investment cost and entry cost induced by open source affect the industry structure and the monetary returns of the PHEV manufacturers. That further allows me to explore the reason why Tesla proposes the open source initiative in the first place.

On the one hand, PHEVs are more willing to invest and to reach better qualities with the decreased investment costs after open source occurs. They would then have higher profits, as PHEVs are competing on the qualities in the product market. On the other hand, lower entry costs allow more competitors to enter the industry. Facing fiercer competition, they may attract fewer consumers and cannot gain as much profit as prior to open source initiative. Depending on which of these two countervailing effects is stronger, PHEV would form different expectations of future returns and make different choices in terms of entry and investment. These decisions will, in turn, determine the future market structure.

In my analysis, I shut down the benefits that open source movement brings and let the PHEVs make the strategic choices accordingly. That is, after the third quarter of 2014, at which point the open source initiative actually occurs, I force the players in the market to face the higher entry costs and unit investment cost as estimated before the open source event. I forward simulate the PHEV industry development until the last quarter of 2017, which is the last period captured in my data. Then I am able to compare the market structure documented in the data with the one generated by the counterfactual analysis. For market structure, I am interested in not only the number of distinct PHEVs, but also the overall market share. Furthermore, I can compute the discounted return for all PHEV players, which consist of investment expenditure, profits from selling their cars and entry expenditure.

However, the forward simulation I apply here requires investment costs and entry costs both remain at the same level as before open source happened. Thus, it cannot clearly show how these two forces affect the market separately. I employ then reduced form analysis to tackle this problem. The total market share of PHEVs of each period serves as a dependent variable, while the unit investment costs and entry costs from last periods enter the equation as covariances. I also control for all the other good reasons why market share would change.

Other than providing an intriguing study on the impact of open source on the development of an industry, this paper also contributes to the string of literature that uses counterfactuals based on a dynamic structural model to analyze policy-relevant events, such as Collard-Wexler (2013); Sweeting (2013); Igami (2015) and Fowlie et al. (2016). Instead of solving equilibrium, I use the estimated policy functions to perform the forward simulation. This approach is only possible based on the assumption, that my counterfactual case happens in the market environment that is exactly the same as the one before the open source event occurs.

Through my counterfactual analysis, I find that Tesla introduces fewer cars in the market and have a lower discounted return, if the industry would have evolved without open source. Less entry is the strategic response to the higher entry costs. Tesla also invests slightly less, but the investment expenditure in total is still higher compared to the one calculated based on the data. The reason is the substantially lower unit investment cost induced by open source. The lower discounted return without technology sharing explains why Tesla proposed open source.

From the point of view of the whole industry, the number of distinct PHEVs in the market drops by 33% due to high entry costs, while the average quality remains more or less the same. That is because the lower-quality PHEVs are more sensitive to the high entry costs and leads to the selection of entrants. The total discounted return (the sum of discounted returns of all PHEVs) is lower in the simulated case, which is the combined result of the high entry and investment costs. The overall profits from all PHEVs are also lower in the counterfactual analysis, while the average across PHEVs is slightly higher. That suggests even though PHEVs profit from the milder competition in the product market, the size of the market (in terms of the number of distinct models) matters more.

The reduced-form analysis reveals how the decreases in unit investment costs and entry costs after the introduction of open source explain the expansion of the market. I find that unit investment cost affects the market share more efficiently compared to entry costs. They account for 22% and 5.3% of the increase in the market share at the end of 2017, respectively.

The remainder of this chapter is organized as follows. I discuss the datasets that I use in section 2.2 and present the model in section 2.3. The policy experiment is described in detail in section 2.4. I discuss the results from the counterfactual analysis in section 2.5 and highlight the contribution on the market share of PHEVs from different sources in section 2.6. Conclusion is presented in section 2.7.

2.2 Data

My data come from a variety of sources. The whole data concerns the US car market from the first quarter of 2012 to the second quarter of 2017. The monthly sales (in quantity) of conventional cars (i.e. gasoline and diesel cars) are from *WardsAuto U.S. light vehicle sales*, which spans from January 2012 until August 2015. I collect the monthly sales of PHEVs from *hybridcars.com*, which cover the periods from beginning of 2012 till the end of 2017. The sales data are aggregated to the quarter level. Then, I supplement these sales data with car physical characteristics and prices data from *MSNAutos* websites. Lastly, I obtain a consumer subjective measure on performance and design for both conventional cars and PHEVs from *JD-Power* and *Consumer Reports*. I discuss each in turn.

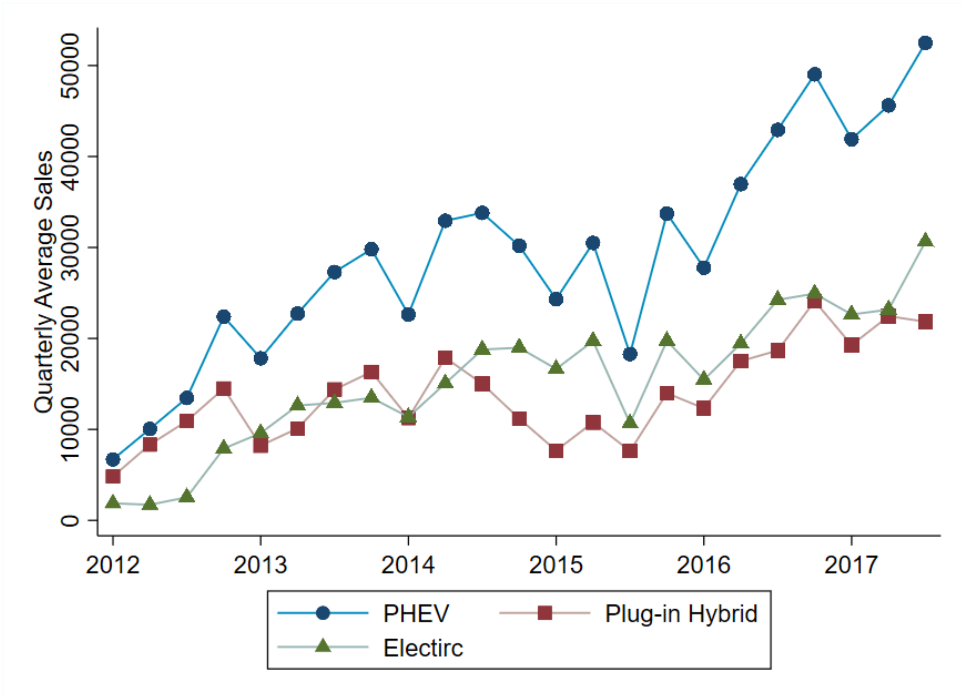
Table 2.1: 10 Car Manufacturers with Highest Total Sales (2012Q1 - 2017Q2)

	Brand	Conventional Cars		Plug-in Hybrid & Electric	
		# Models	Sales (in 1000)	# Models	Sales (in 1000)
1	Toyota	14	5,339	2	44
2	Ford	11	5,253	3	52
3	Chevrolet	14	4,812	2	77
4	Honda	9	4,422	2	2
5	Nissan	13	3,843	1	75
6	Hyundai	10	2,663	0	0
7	Jeep	7	2,212	0	0
8	Kia	8	2,032	1	0.9
9	Subaru	8	1,650	0	0
10	Dodge	8	1,576	0	0

The sales data that covers both conventional cars and PHEVs shows significant reluctance of consumers to purchase this new type of cars. While on average more than 3 million conventional cars are sold in each quarter from the first quarter of 2012 to the second quarter of 2015, the sales of plug-in hybrid cars and electrics cars are only on average 11,440 and 12,100, respectively. Different car manufacturers also shows completely different strategies in terms of the provision of PHEVs. Table 2.1 lists the ten car manufacturers with the highest total sales of cars. Out of these ten manufacturers, four do not provide any PHEV. Among those manufacturers that market PHEVs, they only provide no more than three distinct PHEV models. In contrast, they market on average more than ten conventional car models.

The sales data of PHEVs cover a longer period, i.e. from the first quarter of 2012 to the last quarter of 2017. These data shows a slow upward trend of adoption of PHEVs. Figure 2.1 depicts the quarterly sales of PHEVs over time. The blue round dots represent the combined sales of PHV and EV, while the red square dots and the green triangle dots show the sales of PHV and EV, respectively. Though the sales are increasing already from 2012 till 2015, we see a faster rising after 2015, which could be driven by the open source initiative that was proposed in the end of 2014 by Tesla.

Figure 2.1: Quarterly Sales of Plug-in Hybrid and Electric Vehicles



I web-scrapped the website *MSNAutos* to collect the physical attributes and manufacturer's suggested retail price of the cars that show up in my sales data. As the sales data do not distinguish among the possible several trims that belong to one car model, I use the characteristics of the cheapest trim as the representative characteristics. For instance, I obtain different sales data for Volkswagen Golf and Volkswagen Passat in the first quarter of 2015, but I do not know how much of the sales come from Golf 2.5L FWD and how much from Golf 2.0L TDI. Thus, I take the attributes of Golf 2.5L FWD for all Golf sold in 2015, which is the cheapest one among all available Golf trims in that particular year.

The attributes that I include into my data are size, cargo volume, horsepower per weight, fuel economy, range on highway, and two dummy variables. One describes whether the car has navigation as a standard equipment, and the other one shows whether a car is categorized as PHEV. Size is defined as length times width, and cargo volume determines the space for luggage. Horsepower per weight serves as a proxy for how powerful the engine/motor is. Fuel economy describes how efficient a car is in terms of using gasoline, diesel or electricity. It is defined as miles per gallon (MPG) for conventional cars, as miles per gallon-equivalent electricity (MPGe) for EVs, and as distance-weighted MPG/MPGe for PHVs, i.e. total range/(range with gasoline/MPG + range with electricity/MPGe).[1] Range on highway is the maximum distance a car can achieve on highway, which usually provides the best driving condition. It is calculated for conventional car when its tank is fully filled, and EV when its battery is fully charged. For PHV, I use the combined maximum range by its gasoline/diesel engine and the range by its electric motor.

These physical characteristics together with sales allow me to identify how consumer evaluate each attribute. However, it is common sense that consumers care not only horsepower or fuel economy, but also the comfort or the design. That is the reason I include the consumers evaluation of performance and design (PD) for each car model in each year. I use two data sources for this subjective measure: APEAL (Automotive Performance, Execution and Layout) survey from *JD-Power*, and the wner Satisfaction survey from *Consumer Reports*. In both surveys, consumer are asked to evaluate whether the seats are comfortable, whether the styling of the car is enjoyable, whether the entertainment system (navigation or audio) is easily interactive, etc. This measure ranges from 1 to 5.

After combining characteristics, sales and the price, I obtain my two final datasets. The first dataset spans from the first quarter of 2012 to the second quarter of 2015 and contains both conventional car and PHEVs. I use this dataset to perform the demand estimation and to obtain the taste parameter of each car characteristics and the price sensitivities. The inclusion of the conventional cars indicates that consumers are free to choose across different car categories, which is realistic, and also increases the variation of the data such that I can identify the taste parameters more precisely. I allow the taste parameters to be the same across conventional cars and PHEV models, which is based on the assumption that consumers evaluate these attributes in the similar way across different car categories.

[1] 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*.

My second final dataset spans from the first quarter of 2012 to the last quarter of 2017 and contains only PHEV models. This dataset capture the entry/exit decisions, improvement in physical characteristics, and changes in consumers' subjective measure and prices and thus, documents nicely the industry dynamics. These changes in characteristics together with the taste parameters that are estimated using the first dataset allows me to form the quality evolution of each PHEV models and to perform the analysis of the dynamic supply side.

Table 2.2: Evolution of PHEVs Characteristics (2012-2015)

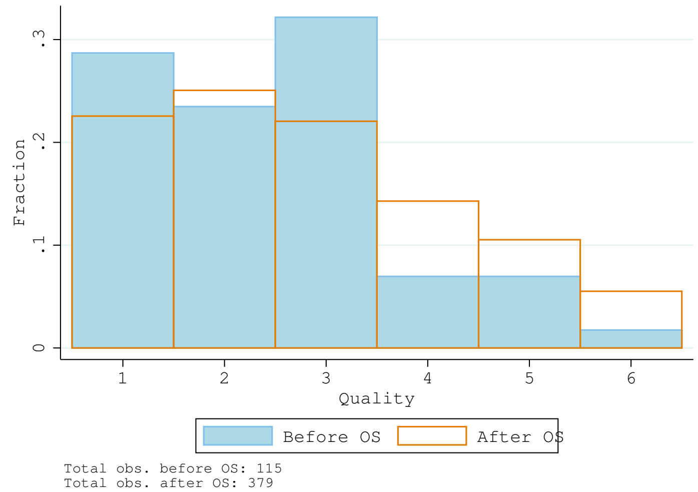
	Price	HP/Weight	MPG(e)	Range (Highway)		Sales	Entry	Exit
				PHV	EV			
2012	**#Model: 9**							
Mean	36.95	0.41	5.78	4.43	1.09	52.61	6	0
Std	5.55	0.10	2.52	0.79	0.75			
2013	**#Model: 16**							
Mean	38.43	0.48	7.39	4.68	1.01	98.79	7	0
Std	11.07	0.18	3.27	0.83	0.31			
2014	**#Model: 22**							
Mean	37.49	0.47	7.84	4.83	1.21	122.47	7	1
Std	15.69	0.17	3.47	0.83	0.54			
2015	**#Model: 26**							
Mean	43.01	0.53	8.22	4.69	1.37	115.98	5	1
Std	20.35	0.20	3.50	0.87	0.57			
2016	**#Model: 31**							
Mean	45.45	0.53	7.32	4.79	1.57	158.71	6	1
Std	19.55	0.14	3.42	0.82	0.58			
2017	**#Model: 40**							
Mean	43.01	0.53	7.57	5.05	1.77	181.53	10	1
Std	17.69	0.13	3.39	1.09	0.56			

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, Sales is in 1000 units.

In Table 2.2 I show the evolution of the PHEV industry from beginning of 2012 to the end of 2017. I present the sales-weighted average prices and characteristics in the first to the fifth columns. Sales and number of car models that enter or exit the market are presented in the column six to eight. I also report the number of PHEVs that are active in the market in each year, which clearly states an expanding of the market, with the amount of active PHEV increasing from only 9 models till 40 models. Overall, both prices and the characteristics show an increasing trend. The increasing standard deviation of prices indicates that the variety of available PHEVs becomes larger over time. The improvement of the characteristics, especially with the striking increasing in the maximum range on highway for both PHVs and

EVs, suggests the qualities of these kind of car also improved over time. Beside there are more PHEVs in the market, the yearly sales also perform a strong increase. In 2017, the sales are more than 3 time higher than the sales in 2012. Each year, I observe some new car models enter the market, while no more than one model exits.

Figure 2.2: Quality Distribution



To have a better illustration of how qualities differ prior to OS and after, I construct the quality level of each PHEV using the taste parameter that obtained from Yan (2020) and the characteristics. There are in total six quality levels, where level one represents the lowest quality and six the highest one. Figure 2.2 shows the distribution of PHEVs prior to and after the open-source initiative in the third quarter of 2014. The blue solid bar represents the qualities before open source and the transparent bar with orange frame are the qualities afterwards. In both periods, I observe that most PHEV models belong to the low-quality category, which is level one to level three. But after open source, there is a a strong shift of the low-quality cars towards high-quality levels. Only around 15% of PHEVs locate in the high-quality levels prior to the open source event, while after this percentage increases to almost 30%.

2.3 Model

To analyse how the PHEV industry would have evolved in the absense of Tesla's open source initiative, I need to specify a dynamic model, which characterizes the behaviors of PHEVs in terms of entry, exit, investment and competition in the product market. The model primitives, timing, and information structure follow from the framework of Yan (2020). In this section, I discuss in detail the model of demand and supply, on which I conduct the policy experiment.

In each period, the events is unfolded in three different stages. In the first stage, potential PHEV entrants decide on whether to enter after observing the private random entry costs. Once they decide to enter, it will take one period for the entrants to setup the production line before engaging in the market competition. At the same time, one of the lowest-quality PHEV incumbents may face an exogenous shock and exit the industry. In the second stage, the remaining PHEV incumbents receive choice-specific shocks on investment and decide whether to invest or not. The outcome of the investment is stochastic, which will only be realized at the end of the period, and the quality of PHEVs evolves according. In the final stage, PHEV incumbents compete in the product market with conventional cars, where consumers make purchase decisions and car manufacturers collect their profits.

I discuss each component in turn.

2.3.1 Demand

As the game can only be solved backward, I start by discussing the last stage of the game – the demand side. I model the demand using a static discrete-choice specification (Berry, 1994), where consumers can choose to purchase a car, whether PHEV or conventional ones, or an outside option, which includes not buying a car or buying a car that is not included in my dataset.[2] As the demand is assumed to be static, I omit the time superscript in discussing the demand model. The indirect utility for a consumer i from buying car j is given by:

$$u_{ij} = \sum_{h=1}^{H} \alpha_h z_{hj} - \alpha_0 p_j + \eta_j + \epsilon_{ij}, \tag{2.1}$$

where z_{hj} denotes the h-th car characteristics such as size, horsepower per weight etc., p_j is the price and η_j represents the car characteristics that are observed by consumers but not by the econometrician. The term ϵ_{ij} is an idiosyncratic taste shock that follows 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, which is a standard assumption in the literature (Berry et al., 1995; Petrin, 2002; Beresteanu and Li, 2011). I further normalized the utility from the outside option u_{i0} to be zero. To identify the taste parameters α_h and price elasticity α_0, I use the the first dataset that spans from the first quarter of 2012 to the second quarter of 2015, which contains sales, prices and attributes of both conventional cars and PHEVs.

[2]It would be more realistic to consider a dynamic demand specification. However, it would greatly increase the computation complexity if it is not unfeasible. Moreover, the main focus and the contribution of this project lie in providing a novel analysis on the entry, exit and investment behaviors of the car industry. Thus, I choose to take a compromise on the demand side.

Giving that consumers choose the cars that give them the highest utility and the distribution assumption of the error term ϵ_{ij}, the market share of car j is

$$s_j = \frac{exp(\sum_{h=1}^{H} \alpha_h z_{hj} - \alpha_0 p_j + \eta_j)}{1 + \sum_{k \in J} exp(\sum_{h=1}^{H} \alpha_h z_{hk} - \alpha_0 p_k + \eta_k)}. \tag{2.2}$$

Using a logit transformation, equation (2.2) can be written as $ln(s_j) - ln(s_i) = \sum_{h=1}^{H} \alpha_h z_{hj} - \alpha_0 p_j + \eta_j$, which can be easily estimated given the information on prices and characteristics of all cars and the assumption that η_j is orthogonal to the observed attributes.

After estimating the demand equations (2.2) and obtain the taste parameters α_h, I can construct the absolute quality of each car as

$$q_j = \sum_{h=1}^{H} \alpha_h z_{hj} + \eta_j, \tag{2.3}$$

which follows the similar approach as (Fan, 2013). In this way, I reduce the cars' heterogeneity from several dimensions to only one and facilitate the further analysis of the dynamic supply model. I then follow Goettler and Gordon (2011) and discretize the absolute quality q_j into quality levels, which is denoted by ω_j. These quality levels are difined as the state variables of each PHEV.

2.3.2 Price Competition

In each period, multi-product car manufacturers choose prices of their cars to maximize their overall profits. The profit of a car manufacturer f is defined as

$$\pi_f(\boldsymbol{p}, \boldsymbol{q}, \boldsymbol{\omega}) = \sum_{j \in J_f} \pi_j(\boldsymbol{p}, \boldsymbol{q}, \boldsymbol{\omega}) = \sum_{j \in J_f} s_j(\boldsymbol{p}, \boldsymbol{q}) M [p_j - c_j(\boldsymbol{\omega})], \tag{2.4}$$

which is the sum of the profit of car j that belongs to the product set J_f of manufacturer f. Vector of prices of these cars are given by $\boldsymbol{p}$, $\boldsymbol{q}$ is the vector of absolute qualities, $\boldsymbol{\omega}$ denotes the vector of quality levels (which is a mapping from $\boldsymbol{q}$), $s_j(\boldsymbol{p}, \boldsymbol{q})$ is given by equation (2.2), M is the market size and $c_j(\boldsymbol{\omega})$ denotes the marginal production cost. I define the market as the the households in the US, who did not purchase any cars in the previous year.

I assume that the marginal costs depends on the quality levels ω_j for both conventional cars and PHEVs in the same fashion, while for the PHEVs, in additional, enjoy the economy of scales effect of the market expending. That is, the marginal cost of PHEVs should decrease with the amount of distinct PHEV models in the market. Thus, the marginal cost mc_j of a car model j can be written as

$$mc_j(\boldsymbol{\omega}) = \begin{cases} \gamma_0\omega_j + \upsilon_j & \text{if } j \text{ is conventional car,} \\ \gamma_0\omega_j + \gamma_1(\sum_{j=1}^{N} \mathbb{1}(PHEV_j = 1)) + \upsilon_j & \text{if } j \text{ is PHEV.} \end{cases} \tag{2.5}$$

where γ_1 measures the effect of economies of scales and υ_j represents the cost driver that is only observed by manufacturers but not the econometrician.

A multi-product car manufacturer choose prices for all its produced cars to maximize the static per-period profit. Therefore, the system of first-order conditions as shown in equation (2.6) has to be satisfied.

$$\frac{\partial \pi_f}{\partial p_j} = M\left(s_j + \sum_{k\in J_f}(p_k - mc_k(\boldsymbol{\omega}))\frac{\partial s_k(\boldsymbol{p},\boldsymbol{q},\boldsymbol{\omega})}{\partial p_j}\right) = 0 \text{ for all } j \in J_f. \tag{2.6}$$

Using equation system (2.6) and demand estimates, I can back out the the marginal costs of all the cars in the market. I then estimate equation (2.5) to obtain the relationship between the marginal costs and the quality levels.

2.3.3 Investment

PHEV has incentive to invest to improve its quality, as it positively affects the market share, and thus, the profit as discussed in the previous two subsections. Whereas the multi-product car manufacturers make the pricing decisions, I assume the investment decision is done by the manager of each PHEV. That is, when the manager decides whether to improve the quality or not, she does not internalize the investment decision of other managers, who serve the same car manufacturers.[3]

The quality changes depends on the costly investments, which is assumed to be a discrete choice $x_j^t \in \{0, 1\}$ and it leads to stochastic results if investment takes place. After observing private choice-specific shocks, $\phi_j^t(x_j^t)$, PHEV incumbents make their investment decisions, where the shocks are assumed to be independent and identically distributed according to the Type I extreme value distribution. Taking into account of the per-period profits from the product market, the investment decision and the choice-specific cost, the per-period payoff of PHEV j is given by

$$\tilde{\pi}_j^t(\boldsymbol{\omega^t}) + C(\omega_j)x_j^t + \phi_j^t(x_j^t), \tag{2.7}$$

[3]This assumption is made based on the discussion with the industry industry. It also facilitate the estimation process.

where $\tilde{\pi}_j^t(\boldsymbol{\omega^t})$ denotes the maximized profit from the market competition and $C(\omega_j)$ is the state-dependent investment cost, which is specified as

$$C(\omega_j) = \bar{c}\,\omega_i^2. \tag{2.8}$$

The underlying assumption of this specification is that it becomes more expensive to make an improvement when the original quality level is high, which is intuitive.

Once the manager of a PHEV model decide to invest, the car may have different levels of improvement. I denote $\tau_j^t = \{0, 1, 2\}$ as the possible levels of improvement, i.e., after investing, the quality level of this PHEV may stay the same ($\tau_j^t = 0$), increase by one or two units ($\tau_j^t = 1$ or 2). These outcomes take place with the following probabilities:

$$\begin{aligned}
p(\tau_j^t = 0 | x_j^t = 1) &= 1 - p(\tau_j^t = 1 | x_j^t = 1) - p(\tau_j^t = 2 | x_j^t = 1), \\
p(\tau_j^t = 1 | x_j^t = 1) &= p_1 + \lambda_1 \mathbb{1}(OS_j = 1), \\
p(\tau_j^t = 2 | x_j^t = 1) &= p_2 + \lambda_2 \mathbb{1}(OS_j = 1),
\end{aligned} \tag{2.9}$$

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

At the end of the period, the investment outcomes are realized. For each PHEV, its quality level (state) evolves in the following fashion:

$$\omega_j^{t+1} = \omega_j^t + \tau_j^t \mathbb{1}(x_j^t = 1) - \mathbb{1}(x_j^t = 0), \tag{2.10}$$

where ω_j^t and ω_j^{t+1} denotes the current quality level and the quality level in the next period, respectively.

I assumed when a PHEV already reaches the highest possible quality level – level six, it can no longer have a successful investment and when a PHEV is at 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.

2.3.4 Potential Entrants

At the beginning of each period t, five potential entrants arrive with randomly drawn quality levels $\omega_j^{(e)t}$ from the distribution $F_\omega^e(\cdot)$.[4] Each potential entrant faces a private random entry cost $\phi_j^{(e)t}$, which is independently and identically distributed across potential PHEV entrants and periods according to a distribution $F_\phi^e(\cdot)$. The potential entrant makes entry decision based on its quality level, the current quality distribution of the incumbents and its private entry cost, which can be denoted as

$$\chi_j^t(\omega_j^{(e)t}, \boldsymbol{\omega}^t, \phi_j^{(e)t}) \in \{0, 1\}, \tag{2.11}$$

where $\chi_j^t(\omega_j^{(e)t}, \boldsymbol{\omega}^t, \phi_j^{(e)t}) = 1$ indicates that potential entrant j with quality level $\omega_j^{(e)t}$ decides to enter the market with the current market structure $\boldsymbol{\omega}^t$, after drawing the entry cost $\phi_j^{(e)t}$. When $\chi_j^t(\omega_j^{(e)t}, \boldsymbol{\omega}^t, \phi_j^{(e)t}) = 0$, it means that the potential entrant decide not to enter. However, when entrant j enters the market, it will not participate in the product market competition at time t neither can it invest in improving quality. The entrants have to use this whole period to set up the production line with payment $\phi_j^{(e)t}$ and become an incumbent in the next period $t+1$. Unlike the incumbents, potential entrants are short-lived. If they do not enter the industry, they receive nothing and vanish. As potential PHEV entrant makes the entry decision based on the private information on quality level and entry cost, the incumbent PHEV can only form expectation of the probability that one new PHEV enters the industry. The probability is denoted by

$$\xi_j^{(e)t}(\boldsymbol{\omega}^t) \equiv prob(\chi_j^t(\omega_j^{(e)t}, \boldsymbol{\omega}^t, \phi_j^{(e)t}) = 1) = \int\int \chi_j^t(\boldsymbol{\omega}^t, \phi_j^{(e)t}) dF_\phi^e(\phi_j^e) dF_\omega^e(\omega_j^e) \tag{2.12}$$

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

2.3.5 Exit

Simultaneously to entry, at the beginning of each period, exit may also occur. However, I assume that the exit is an exogenous event and only one incumbent with the lowest quality level may leave the industry. Such assumptions are motivated by data, where exit is rarely observed. Exit happens with probability ψ and the lowest-quality PHEV incumbents face the

[4] 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. The pool of quality levels of the potential entrants is given by the empirical distribution of the observed entrants in the data.

same probability of exiting. For instance, if there are three incumbents in quality level one, which is the lowest possible state, then each of them has a probability of $\psi/3$ to exit.

2.3.6 Equilibrium

In each period t, PHEVs makes entry and investment decisions to maximize its discounted future returns, taking into account that the pricing decisions is made by multi-product car manufacturers in a myopic fashion. That yields the value function of incumbent PHEV j, when facing the investment decision:

$$
\begin{aligned}
V_j^t(\boldsymbol{\omega}^t, \phi_j^t) = \max_{x_j^t \in \{0,1\}} \Big\{ & \tilde{\pi}_j^t(\boldsymbol{\omega^t}) + C(\omega_j)x_j^t + \phi_j^t(x_j^t) \\
& + \beta E\{V_j^{t+1}(\boldsymbol{\omega}^{t+1}, \phi_j^{t+1}) | \boldsymbol{\omega}^t, \omega_j^{t+1} \neq 0, x_j^t(\boldsymbol{\omega}^t), x_{-j}^t(\boldsymbol{\omega}^t), \xi_{-j}^{(e)t}(\boldsymbol{\omega}^t)\} \Big\}
\end{aligned}
\tag{2.13}
$$

where the first line represents the per-period return as discussed in equation (2.7) and the second line denotes the expectation of the discounted future value function. This expectation is taken with respect to j's investment outcome (τ_j^t), j's rivals' investment decisions ($x_{-j}^t(\boldsymbol{\omega}^t)$), potential entrants' decisions ($\xi_{-j}^{(e)t}(\boldsymbol{\omega}^t)$) and that j remain in the industry ($\omega_j^{t+1} \neq 0$). The discount rate β takes the value of 0.925.

Potential PHEV entrant only enters, when the expected discounted future return exceeds the randomly drawn entry cost. The value function of a potential entrant j is given by

$$
\begin{aligned}
V_j^{(e)t}(\boldsymbol{\omega}^t, \phi_j^{(e)t}) = \max_{\chi_j^{(e)t} \in \{0,1\}} \Big\{ & \chi_j^{(e)t} \\
\Big(- \phi_j^{(e)t} + \beta E\{V_j^{t+1}(\boldsymbol{\omega}^{t+1}, \phi_j^{t+1}) | \boldsymbol{\omega}^t, \omega_j^{t+1} \neq 0, & x_{-j}^t(\boldsymbol{\omega}^t, \xi_{-j}^{(e)t}(\boldsymbol{\omega}^t))\} \Big) \Big\}
\end{aligned}
\tag{2.14}
$$

where the expectation term is essentially the same as the incumbent if the entry occurs ($\omega_j^{t+1} \neq 0$). The differences lie in the fact that the entrant makes no investment and cannot compete in the product market. Instead, it pays the randomly drawn entry costs ($\phi_j^{(e)t}$), where $\chi_j^{(e)t}$ denotes the entry choice.

I assume PHEVs use symmetric strategies that depend solely on the current industry state, their own state, the unit investment cost and their randomly drawn entry costs/investment-choice-specific shocks, leading to a Markov-Perfect Nash Equilibrium (Ericson and Pakes, 1995; Maskin and Tirole, 1988). For ease of exposition, I omit all time subscripts, as time does not play a role in the optimal strategy.

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

$$V_j(\boldsymbol{\omega}, \phi_j; \sigma_j, \sigma_{-j}) \geq V_j(\boldsymbol{\omega}, \phi_j; \sigma', \sigma_{-j}), \tag{2.15}$$

for all PHEV j, all states $\boldsymbol{\omega}$, all shocks ϕ and all possible alternative strategies σ'. The existence of a pure-strategy equilibrium is guarantee by these private shocks (Doraszelski and Satterthwaite, 2010).

2.4 Policy Experiment and Simulation Procedure

The estimates of the above-described model are presented and discussed in Yan (2020). It shows a sharp decrease in unit investment cost and a slight fall in entry cost after Tesla proposed its open source initiative. However, Tesla does not enjoy a direct benefit from the open source, as its innovation advantage due to the familiarity with its own shared technology is estimated to be insignificant from zero. The estimation results also confirm the existence of the effect of economies of scale in the PHEV industry.

Several questions remain unanswered in Yan (2020): 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.[5]

[5]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

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 2.3. 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, random 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 (2.5), 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 (2.7). At the end of the period, I draw the realization of the investment outcomes according to the estimation of the equation (2.9) and each PHEV evolves as (2.10) 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.

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.

2.5 Results

2.5.1 Tesla's Profit

To understand why Tesla use open source, I compute the simulated discounted return of Tesla in the scenario as described in section 2.4,

$$V_{Tesla}^{2014Q3-2017Q4} = \sum_{t=2014Q3}^{2017Q4} \sum_{j \in Tesla} \beta^t \Big(\mathbb{1}(j \in incumbent)(\tilde{\pi}_j^t(\hat{\boldsymbol{\omega}}^{\boldsymbol{t}}) + C(\hat{\omega}_j)\hat{x}_j^t + \phi_j^t(\hat{x}_j^t)) \tag{2.16}$$
$$+ \mathbb{1}(j \in entrant)\hat{\chi}_j^{(e)t}(-\phi_j^{(e)t}), \Big)$$

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 (2.16). 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 2.3 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 2.3. 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 2.3: 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)

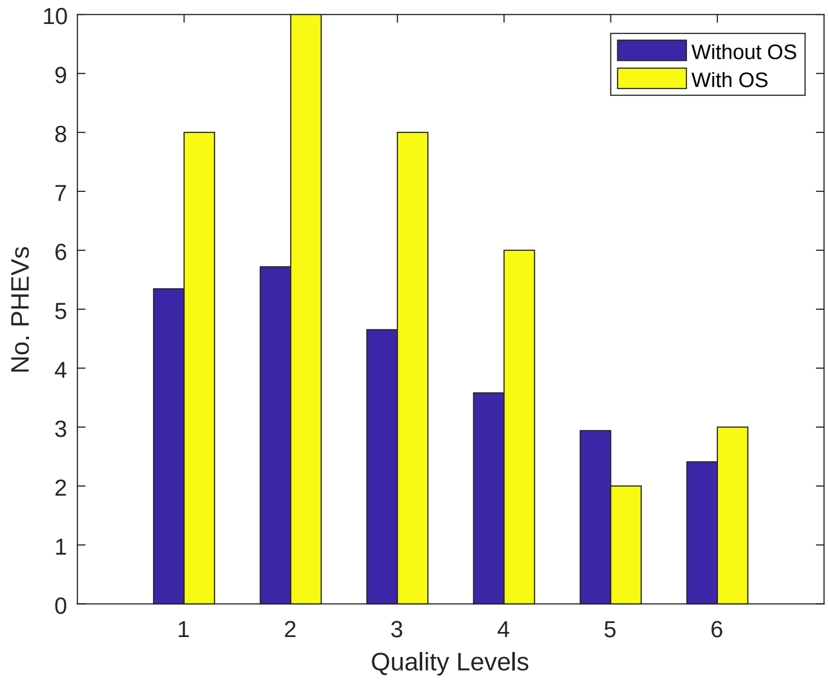
Standard errors in parentheses

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 in section 2.4, 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 2.3 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.

2.5.2 Industry Structure

Using the same simulation process as described in section 2.4, 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 2.3.

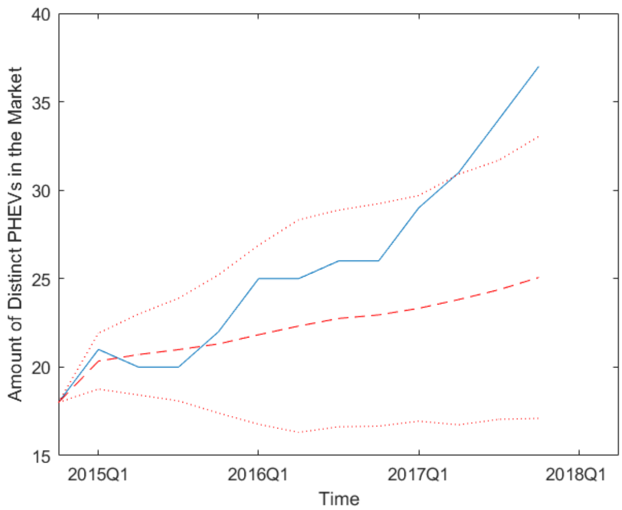
Figure 2.3: Quality Level Distribution of PHEVs in 2017 Q4



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 2.4 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.

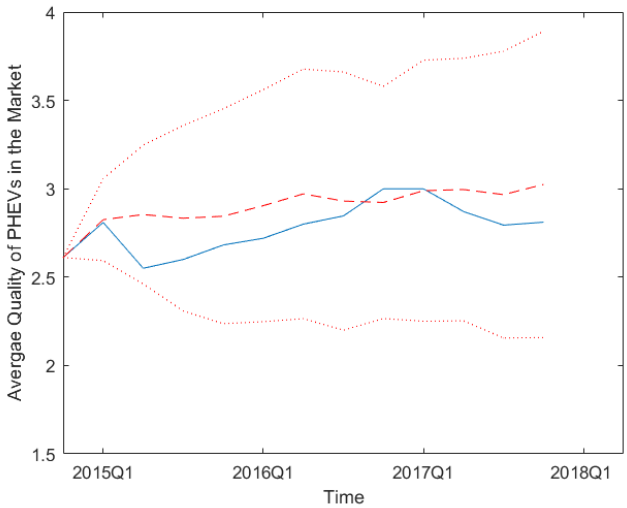
Figure 2.4: Number of PHEVs in Data and in Counterfactual 2014Q3 – 2017Q4



I show the quality dynamics in Figure 2.5, 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 2.3). 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.

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 2.4. 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.

Figure 2.5: Quality of PHEVs 2014Q3 – 2017Q4



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 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.

Table 2.4: 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

Other than the statistics I present in Table 2.4, 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.

2.6 Contribution on Market Share

As discussed in the last section, open source leads to a higher market share of PHEVs, and it can be driven by different sources, as described in section 2.3. Lower entry costs attract more entrants, providing the consumers with a broader choice set and potentially leading to higher PHEV market share. The low investment gives the incumbents a higher incentive to invest and to improve the car's quality, which could attract the consumers away from conventional cars and induce a higher market share of PHEV. To separate these two strings of effects, I run the following regression:

$$MS_t = \alpha_1 q_{jt} + \alpha_2 IC_{t-1} + \alpha_3 EC_{t-1} + \delta_{J_f} + \delta_t \tag{2.17}$$

where MS_t is the market share of all PHEVs in the market at time t, i.e., $MS_t = \sum_j s_{jt}$, q_{jt} is the quality level of PHEV j at time t, IC_{t-1} and EC_{t-1} denote the unit investment cost and entry cost from the last period $t-1$, δ_{J_f} captures the fixed effect induced by the manufacturer f that produces car j, and δ_t is the year fixed effect.

The unit investment cost is the same for all observations in a given period. That means, the unit investment cost is constantly 16.68 million dollars before open source, while it decreases to 6.61 million dollars afterward. This variable serves as a proxy of how likely the incumbents are going to invest in the previous period and determines the overall competitiveness of PHEVs with respect to other means of transportation.

The entry costs are drawn from the estimated cost distribution. To be consistent with the assumption in the model, that five potential entrants arrive in each period, I randomly draw for each period five entry costs. Prior to open source initiative took place, I draw from the uniform distribution [$555, $595] million and from [$460, $520] million afterward. Then, I assign these five entry costs randomly to the observation in the next period. This variable captures how likely the potential entrants will enter the market, which partially determines the market structure of PHEV in the current period in terms of how many distinct PHEV models are available in the market for the consumers.

I present the estimation results in Table 2.5, where I show in total seven specifications. The dependent variables are quarterly market shares of all PHEVs in 0.0001 from the first quarter of 2012 until the last quarter of 2017. The regressors are the quality levels of each PHEVs in each quarter, unit investment costs, randomly drawn entry costs, and a constant. In specification five and six, I also include manufacturer fixed effect and year fixed effect separately. I then include both fixed effects in the last specification. The fixed effect of the manufacturer controls for the possible increase in market share induced by brand loyalty. Time fixed effect is used to rule out the unobserved market environment changes, e.g., consumers become more familiar with these new types of cars and more willing to adopt it even though there is no substantial improvement in the quality.

Table 2.5: PHEV Market Share: Quality, Investment and Entry Cost

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Quarterly Market Share of PHEV (in 0.0001)						
Quality	0.231**	0.116	0.157*	0.141	0.122	0.0677	0.162
	(0.117)	(0.0968)	(0.0924)	(0.0923)	(0.164)	(0.0663)	(0.120)
Unit Investment Cost (M$)		-0.445***		-0.126**	-0.0798	-0.386***	-0.373***
		(0.0305)		(0.0550)	(0.0573)	(0.0598)	(0.0629)
Entry Cost (100M$)			-5.174***	-4.027***	-3.957***	-1.120**	-1.178**
			(0.313)	(0.590)	(0.602)	(0.454)	(0.470)
Constant	12.55***	17.10***	39.60***	34.89***	35.40***	18.87***	18.92***
	(0.365)	(0.433)	(1.662)	(2.639)	(2.869)	(2.186)	(2.412)
Brand FE	No	No	No	No	Yes	No	Yes
Year FE	No	No	No	No	No	Yes	Yes
Observations	451	451	451	451	451	451	451
Adjusted R^2	0.006	0.325	0.381	0.387	0.390	0.686	0.675

Standard errors in parentheses

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

Quality shows a significantly positive effect on the overall market share of PHEV in the first specification, which can be interpreted as an increase of the average quality leads to a higher market share of the PHEV industry as a whole. However, this effect shrinks both by size and significance when I include entry cost from the last period, and then completely fades away as soon as I include unit investment cost. This suggests that the average quality improvement are driven by the decrease in the investment cost and entry cost.

The coefficients of unit investment cost and entry cost are both negative and significant, even after controlling for both manufacturer fixed effect and year fixed effect. While one million dollars decrease in unit investment cost leads to a 0.000037 increase in the overall market share of PHEV, a hundred million decrease in entry cost causes an increase of the market share of approximately 0.00012.

Use the most complete specification – the seventh specification, I can conduct a back-of-the-envelope calculation to compare the effectiveness of the decrease in investment cost and the reduction in entry cost in terms of helping the PHEV industry to expand. After Tesla proposed its open source initiative, the unit investment cost drops by 10.17 million dollars, which leads to a 0.037 percentage point increase of the market share. Entry cost falls by on average 80 million dollars, which means that the market share will increase by 0.009 percentage points according to my estimates.

Recall that the definition of the market share is the total number of PHEV being sold in one quarter over the number of households in the US, who does not make any purchase of cars in the previous year. Based on this definition, the market share of PHEV is merely 0.02% at the beginning of 2014 and reaches 0.19% in the end of 2017. Even though the magnitudes of the unit investment cost and entry cost seem small, they actually account for 22% (i.e., 0.037% / 0.17%) and 5.3% (i.e., 0.009% / 0.17%) of the market share changes in 2017 compared to the one in 2014, respectively.

2.7 Conclusion

In this paper, I use the framework and estimation proposed and employed in Yan (2020) to conduct a counterfactual analysis, where Tesla does not share the technology with its competitors. More precisely, I forward simulate the PHEVs strategic behavior of entry and investment under the assumption that the entry cost distribution and unit investment cost are as high as before open source took place. In addition, I perform a reduced-form analysis using the estimates from Yan (2020) to distinguish the effect of these two costs on the market expansion.

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.

The regressions imply that investment costs have a more substantial effect than the entry cost on the overall market share of PHEVs. While one million dollars decrease in unit investment cost leads to a 3.7×10^{-5} increase in the market share, a million decrease in entry cost causes an increase in the market share of approximately 1.2×10^{-6}.

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 both analysis suggests that a reduction in the investment costs is essential for a better development of the industry.

3 The Pre-emptive Effects of Advertising: Dynamics in the CPU Industry

joint with Michelle Sovinsky

3.1 Introduction

Generally, preemptive behaviors refer to various measures that an incumbent firm takes to defer rivals from entering the market or inhibiting the rivals from competing. Among others, predatory pricing is the most prevalent. It is a price reduction that is profitable only because of its preemptive effect. However, other non-price predations are also not rare. Preemptive investments, such as excessive capacity, product differentiation or advertising, have a similar objective as predatory pricing that would weaken or eliminate competitors. In this paper, we focus on excessive advertising as a preemptive tool.

It is challenging to test whether advertisements are used in an anticompetitive fashion. Advertising, as part of the marketing program, helps to build brand reputation and loyalty. Thus, it is generally believed to build goodwill, and this may be a reason to invest in marketing in the absence of anticompetitive motives.

To tackle this problem empirically, we look at a compelling case from the microprocessor industry. As a dominant manufacturer, Intel launched a marketing campaign where it promised a percentage rebate for downstream PC producers that market Intel-based computers. We use market-level data on PC sales and characteristics, CPU sales and characteristics, PC and CPU advertising expenditures, and CPU prices to examine whether Intel used advertising in a different way for firms that were in an illegal relationship with them via exclusive deals, after controlling for all the other good reasons one could advertise. Especially, we incorporate the dynamic nature of advertising, i.e., the advertisement today will have an impact on consumers' purchase decisions tomorrow. Without taking into account the long-run effect of advertising, we may underestimate the profitability of using marketing/advertising campaigns and leads to a different conclusion in terms of whether that is anticompetitive behavior.

While there is a vast theoretical literature on preemptive behaviors, there are relatively few empirical studies, and these focus mainly on pricing predation. Related papers in the preemption literature include: Weiman and Levin (1994) examine predatory pricing by Southern Bell Telephone Company when independent phone companies were trying to enter the market during the period 1894 to 1912. Granitz and Klein (1996) provide evidence that Standard Oil engaged in preemptive behavior by threatening to withhold inputs from railroads that were not in the railroad cartel. Genesove and Mullin (2006) find the price-cost margin was negative in the sugar industry during price wars. Such preemptive behavior was used as a tool to establish a reputation as a tough competitor and, thus, profitable. Morton (2000) test whether pharmaceutical manufacturers use advertising to deter generic entry prior to patent expiration, and Ellison and Ellison (2011) examine how investment serves as an entry deterrence behavior in the same circumstance and focus on the asymmetry in detailing activities in markets of different size. Similarly, Chen and Tan (2007) focus on whether detailing in the pharmaceutical industry is consistent with preemptive incentives. Finally, Snider (2009) and Besanko et al. (2014) estimate dynamic models of predatory pricing. While the first one assesses the impact of predation policies in the airline industry, the latter disentangle aggressive pricing from pursuing efficiency when there is learning-by-doing. Igami (2017) studies the preemptive behavior of hard disk drive manufacturers between 1981 and 1998, with a focus on investment and quality improvement. He finds that the cannibalization effect outweighs the preemptive effect on incumbents.

Our work contributes to the stream of research that examines the dynamic effects of advertising. These include papers by Salgado (2008b). Finally, we estimate the impact of advertising in the CPU and PC market, which is related to work by Eizenberg et al. (2017),Sovinsky Goeree (2008) and Salgado (2008a).

We find that CPU firms benefit from the advertisement expenditure in terms of quarterly revenue, with Intel having substantially higher return than AMD. We also confirm that advertising has a long run impact. As the estimation shows, even advertising from three quarters earlier have a significant and positive effect on CPU firms' revenue. By comparing return patterns from different types of firms and in different periods, the estimation results support our hypothesis that Intel use advertising in a different way for firms that engage in an exclusive-dealing relation with Intel.

This paper is structured as follows. We introduce the Intel Inside campaign in section 3.2 and discuss the data we use in section 3.3. In Section 3.4, we present the estimation strategy.

The results are discussed in section 3.5 and robustness checks are provided in section 3.6. We finally draw conclusion in section 3.7.

3.2 Background

Intel has been investigated for predatory (pricing), exclusionary behavior, and the abuse of a dominant position in the market for central processing units (CPU). According to U.S. lawsuits, Intel used marketing loyalty rebates, payments, and threats to persuade computer manufacturers, including Dell and Hewlett-Packard (HP), to limit their use of AMD (Intel's main rival) processors. In their investigations, U.S. antitrust authorities focused on whether the loyalty rebates used by Intel were a predatory device in violation of the Sherman Act. The European Commission (EC) brought similar charges and imposed a 1.06 billion Euro fine on Intel for abuse of a dominant position. South Korean and Japanese antitrust authorities also imposed fines on Intel for breach of antitrust regulations.

In the case of Intel, an important component to the case involved their marketing campaign, "Intel Inside", which provided marketing support for firms that sold Intel CPU chips. Specifically, it is a cooperative advertising program in which Intel contributes a percentage of the purchase price of processors to a pool for PC firms to use to market Intel-based computers. According to the rules of the program PC firms can receive a rebate of their marketing expenditures if they include the Intel logo in their advertising. By the end of the 1990s, Intel had spent more than $7 billion on the marketing campaign (Moon and Darwall, 2002).

Intel was accused of using the marketing program to attempt to prevent computer makers from offering machines with non-Intel computer chips. It became clear through correspondence that Intel was trying to circumvent antitrust laws by using non-price predatory avenues. For example, a 2002 Dell document states that the "original basis for the [Intel marketing] fund is ... Dell's loyalty to Intel". The document explains that this means "no AMD processors".[1] The beginning of the alleged anticompetitive use of the Intel Inside program coincides with the introduction by their main rival AMD's Athlon chip (in 1999). Antitrust documentation shows that Intel issued "conditional rebates" from December 2002 to December 2005, whereby they would give rebates to some PC firms (Dell in particular) under the condition that the PC firm buy exclusively from Intel.[2] Otherwise, Intel would retract the marketing rebate and instead use the market development money to fund competitors. An internal Dell presentation (in 2003) noted that if Dell switched to AMD, Intel's retaliation "could be severe and prolonged

[1] US District Court for the District of Delaware Complaint. 2009

[2] U.S. District of Court for District of Columbia; SEC (Securities and Exchange Commission) vs. Dell, pp. 10-11 and U.S. District of Court for District of Delaware; State of New York, by Attorney General Andrew M. Cuomo vs. Intel Corporation, p.6.

with impact to all LOBs [Lines of Business]". Intel allegedly treated HP, Lenovo, and Acer similarly. For example, Intel rebates were conditional on HP buying 95% of its microprocessors for business desktops from Intel. In 2002, an HP executive wrote "PLEASE DO NOT … communicate to the regions, your team members or AMD that we are constrained to 5% AMD by pursuing the Intel agreement".

Intel's major (and only effective) rival is AMD, holding about 18 percent market share (Mercury Research, 2007). In 1999 and 2003, respectively, AMD introduced two new chips, the Athlon for personal computers and the Opteron for servers. These AMD chips were the high-end products intended to compete with Intel. By introducing these 64-bit processors, AMD enabled PC operating systems to handle large amounts of information more fastly and accurately (as compared to a 32-bit OS system). These attributes were welcomed by experts and consumers and it was generally agreed that these AMD chips were better-performing and cheaper than Intel counterparts. The case files denote that the Athlon *"was almost universally recognized as being superior to Intel's then current top model for PCs, the Pentium III"* (pp.14-15, Complaint, US District Court of Columbia, SEC vs. Dell) and that *"Opteron garnered virtually unanimous industry acclaim; AMD had succeeded with an innovative product design yielding performance advantages which effectively "leapfrogged" Intel "* (pp.14-15, Complaint, US District Court of Delaware, State of New York vs. Intel). The threat of new, high-performance processors from AMD may have induced Intel to engage in anticompetitive actions. These events provide the motive for Intel's predatory behavior. Indeed, many jurisdictions in the world accused Intel of using various anticompetitive tactics against AMD starting in 2002.

To remain as a valid competitor in a rapidly changing, high-technology industry like the CPU industry, firms need to secure constant cash flows and keep investing in innovation. The CPU industry is capital-intensive, hence firms will incur substantial costs to construct and maintain fabrication units (called "fabs"). If a firm does not have sufficient internal funding, it must obtain external funding at market rates. According to industry experts, Intel is able to fund its fabs with revenue, while AMD must secure funding at market rates, which significantly raises AMD's cost of capital. Furthermore, obtaining external financing is complicated due to agency problems. Typically investors require firms to show a positive prospect of future profits, which is often based on current performance. Preemption would make the future prospect of the prey look lower (and potentially negative) and ultimately induce it to exit the market. Thus, preemption in the CPU market would be consistent with the long-purse (deep-pocket) theory of predation.

Second, since firms are continuously innovating, they may be uncertain about how consumers will react to new products. New processors can have different characteristics possibly appealing to a different market segment from current customers. As mentioned before, the beginning of the anticompetitive use of the marketing program coincides with AMD's introduction of high-performance chips. By engaging in preemptive behavior, Intel could send a (wrong) signal about the demand for new chips, which is consistent with the demand signaling theory (test-market theory) of predation.

Lastly, economies of scale exist in the CPU industry. The substantial investment in plants and technologies are sunk. Therefore, a firm needs to secure a certain amount of sales in order to recover the sunk costs and stay in business. It is easier for a dominant firm to exclude a rival and prevent new entrants in the presence of economies of scale. In this sense, preemption is likely to be successful in driving AMD out of a market and Intel is likely to keep high profit margins for a sufficiently long time.

The CPU industry is inviting to preemptive behavior for these reasons, and Intel is an incumbent with a dominant market share. Given that Intel's recoupment is very likely as a monopolist due to high entry barriers and that preemption can successfully lead to exclude AMD in the CPU industry, showing sacrifice of short term profits would support that the marketing program is predatory.

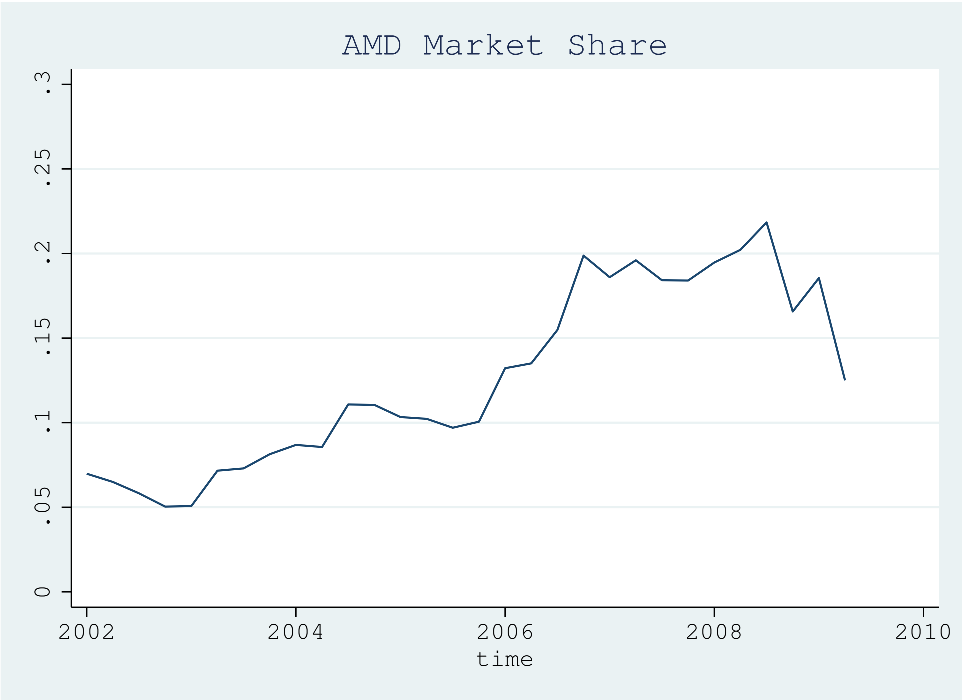
Price and quantity are not the only strategic variables that can be used for anticompetitive purposes. Advertising is another important strategic variable commonly employed by firms. However, antitrust authorities typically try to establish anticompetitiveness through pricing, but do not address the strategic use of advertising and, more generally, marketing campaigns. While the heart of the anticompetitive actions of Intel was their Intel-Inside marketing program, considerations of advertising/marketing preemption where not at the forefront of the antitrust case. In this paper we focus on non-price anticompetitive behavior arising from marketing/advertising with a focus on the Intel case.

3.3 Data

We use several data sources for our analysis: PC and CPU sales are from Gartner Group, CPU price data are from In-Stat and online websites, CPU quality measures are from Passmark's CPU benchmark publication, advertising data are from Kantar Media Group. All data are available from the first quarter of 2002 through the second quarter of 2009. We discuss each in turn.

Quarterly PC and CPU sales are at the product level. A CPU product is defined as CPU vendor (i.e., Intel), CPU family (i.e., Pentium 4), CPU speed, market(i.e., home, education, government or business), platform group (e.g., whether is used for deskbased or mobile PC) and detailed platform types (e.g., all–in–one for deskbased PC and Tablet PC for mobile PC) combination.[3] A PC product is defined as PC firm (i.e., Acer), PC brand (i.e., Aspire), and CPU product combination. We aggregate the data to the level of PC firm, PC brand, CPU vendor, CPU family, market and platform group combination and treat the quarterly such combination as our observation. We show the descriptive statistics in table 3.1. The total number of observations is 23,086, among which 5668 products use AMD's chips. The PC sales (in quantity) per quarter is on average 9550 units and PCs equipped with AMD chips have a slightly lower sales than the one equipped with Intel chips. To illustrate how well AMD is adopted by PC firms and consumers, we compute the quarterly market share of PC with AMD chips over time, where the market share is defined as the total shipment of PCs that use AMD chips over the total shipment of all kinds of PC in a quarter. Figure 3.1 shows that only about 7% of PC sales are generated by PC with AMD chips at the beginning of 2002 and it increases dramatically after 2005 up till more than 20%.

Figure 3.1: Market Share of PC with AMD Chip over Time



CPU prices data come from In-Stat and list prices publication. In-Stat provides data on CPU prices for selected processors of Intel, which are available by processor core on a quarterly basis. The same processor core is often used to make CPUs that are marketed under different family names with different sets of features enabled, and the processor core used in a CPU changes over time as technology advances. For instance, processor core "Banias" was used for CPU families marketed as Celeron M and Pentium M for mobile computers, while in later periods

[3] CPU speed is only available till the first quarter of 2005.

Table 3.1: Descriptive statistics

	Obs	Mean	Std. Dev.	Min	Max
Overall					
Contains AMD CPU	23086	0.25	0.43	0.00	1.00
PC Shipment (in 1000 Unit)	23086	9.55	31.07	0.00	732.37
CPU Shipment (in 1M Unit)	23086	0.19	0.36	0.00	2.88
Price CPU (100$)	23086	1.50	0.70	0.22	6.13
CPU Revenue (in 10M$)	23086	3.03	6.57	0.00	59.59
CPU Benchmark (in 1000)	23086	0.69	0.59	0.17	6.45
PC Firm Advertising (10M$)	23086	0.92	1.95	0.00	9.38
PC Brand Advertising (10M$)	23086	0.08	0.24	0.00	2.94
CPU Vendor Advertising (10M$)	23086	0.52	0.66	0.02	4.12
CPU Family Advertising (10M$)	23086	0.07	0.21	0.00	1.71
AMD					
PC Shipment (in 1000 Unit)	5668	8.56	26.53	0.00	394.71
CPU Shipment (in 1M Unit)	5668	0.09	0.13	0.00	0.64
Price CPU (100$)	5668	1.27	0.82	0.24	6.13
CPU Revenue (in 10M$)	5668	1.04	1.60	0.00	8.47
CPU Benchmark (in 1000)	5668	0.79	0.50	0.27	3.50
CPU Benchmark/Dollar	5668	8.23	6.47	1.78	31.19
PC Firm Advertising (10M$)	5668	1.08	2.09	0.00	9.38
PC Brand Advertising (10M$)	5668	0.06	0.19	0.00	1.79
CPU Vendor Advertising (10M$)	5668	0.10	0.08	0.02	0.50
CPU Family Advertising (10M$)	5668	0.04	0.17	0.00	1.71
Intel					
PC Shipment (in 1000 Unit)	17418	9.87	32.40	0.00	732.37
CPU Shipment (in 1M Unit)	17418	0.22	0.40	0.00	2.88
Price CPU (100$)	17418	1.58	0.64	0.22	4.76
CPU Revenue (in 10M$)	17418	3.67	7.39	0.00	59.59
CPU Benchmark (in 1000)	17418	0.66	0.62	0.17	6.45
CPU Benchmark/Dollar	17418	5.05	5.12	1.14	35.77
PC Firm Advertising (10M$)	17418	0.87	1.89	0.00	9.38
PC Brand Advertising (10M$)	17418	0.09	0.26	0.00	2.94
CPU Vendor Advertising (10M$)	17418	0.66	0.71	0.08	4.12
CPU Family Advertising (10M$)	17418	0.08	0.22	0.00	1.70

All monetary terms were deflated to 2000 dollars using Consumer Price Index (CPI) data from the Bureau of Labor Statistics.

the same CPU families switched to the next-generation processor core "Dothan"Ṫo match these data with the sales data from Gartner group, we use the product cross-reference in Table A.1 in the appendix.[4] We match the data based on platform group (whether desktop or mobile), platform type (e.g. All–in–One, Deskbound, Desktop Replacement, etc.), family/marketing name of a CPU, CPU speed, year, and quarter.[5] We present an overview of available CPUs from In-Stat dataset and their price variation on the CPU family level in Table A.2 in the appendix.

Intel's list prices are collected from Intel's price catalogs, spanning from the last quarter of 2005 to the second quarter of 2009, while AMD's list prices are collected from its website using waybackmacine.com with a time period from the beginning of 2002 to the second quarter of 2009. Both list price data are published at the CPU model level (e.g., Intel Celeron D processor 340 Desktop), which contains CPU family name, model code and platform group. If we have several observation for one CPU model in a quarter, we take the median to form the quarterly CPU price. Intel's list price data further contains CPU speed for most observations, whereas AMD's not. But their detailed information of the model name (e.g. AMD Athlon XP Processor Mobile 1600+) allows us to assign the corresponding platform group and speed to each observation.[6] We then match these price data to the sales data from Gartner Group based on CPU family name, CPU speed, platform group, year and quarter.[7] If one observation in Gartner data has several matches of list prices, we take the average of them. Table A.3 in the appendix provides an overview of price variation on the CPU family level obtained from list prices.

We show in Table 3.2 the combined CPU prices from In-Stat and list prices by CPU vendors (i.e. Intel and AMD) and CPU families. CPU prices display significant variation, ranging from $22 to $613. It is also notable, that Intel's CPUs are on average more expensive than the AMD (as indicated in Table 3.1), with a higher variation across different CPU families. Within

[4]The cross-reference table is constructed based on In-Stat's document and a website specialized in CPU information, www.cpu-world.com.

[5]This process (and a slight generalization of it described below) generates a high match. For the CPUs not matched at the first attempt, we drop CPU speed, then we have 82% match. When unmatched, the data are matched based on family/marketing name of a CPU, platform group, year, and quarter, ignoring platform types. Then we obtain a 84% match. When the data are not matched, we try matching based on family/marketing name of a CPU, year and quarter, ignoring platform group, and then we have 92% match. lastly, we match two datasets based on CPU family name, platform group, platform type, ignoring time, and then we obtain 95% match. For observations still not matched, we take the averages of prices and cost estimates of CPUs of the same marketing name, year and quarter.

[6]We use the data provided by ww.cpubenchmark.net and www.cpu-world.com.

[7]If the first match does not succeed, we drop speed and then perform the matching according to CPU family name, platform group, year and quarter. If it is still not matched, we try to match based on only CPU family name, year and quarter. For the rest unmatched observation, we fill in the prices depending on the location of the missing. If the price is missing either at the beginning or at the end of the sequence, we replace them using the first or last observed prices. If it is missing in the middle, we approximate the price by linear interpolation at the family-platform group level.

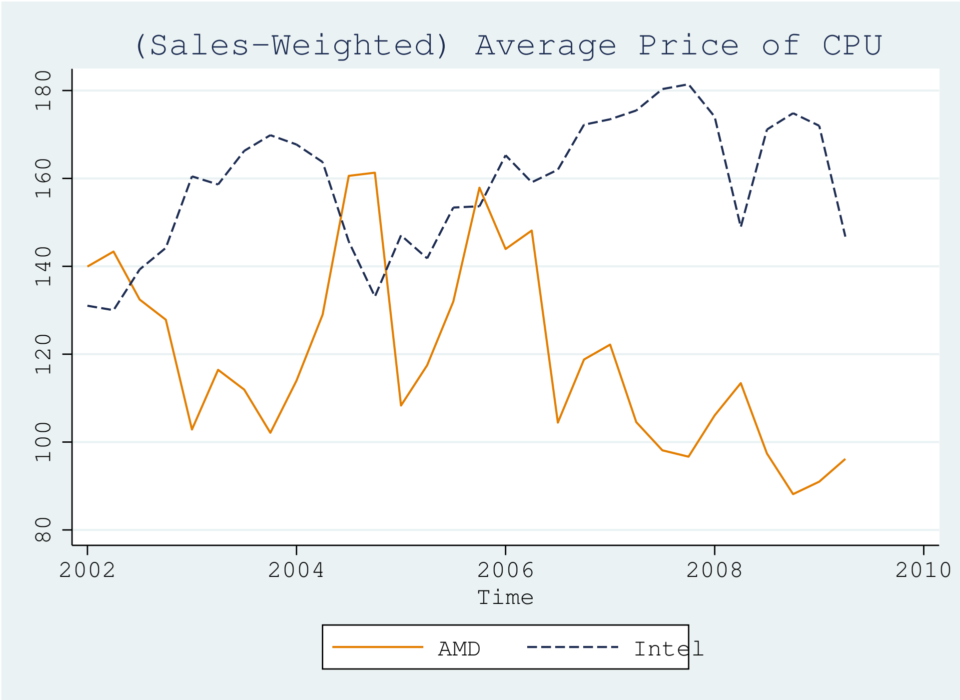
family price variations can be explained by the distinct prices of CPUs with different speed and also by the fact, that a new CPU is usually introduced into the market with a higher price and experience a strong decline over time. Figure 3.2 illustrates how the PC sales-weighted average CPU prices change over time for each CPU vendor. AMD's average CPU price is almost constantly lower than Intel's, with exceptions at the beginning of our data period and two spikes of AMD that are induced by the introduction of Athlon 64 and Athlon 64 X2.

Table 3.2: CPU Price in $100

CPU Firm	CPU Family	Median	Std Dev	Min	Max	Obs
	Ath	0.92	0.35	0.55	2.07	818
	Ath 64	1.43	0.73	0.29	3.21	1151
	Ath 64 X2	1.19	1.35	0.49	6.13	1120
	Dur	0.66	0.15	0.38	0.89	108
	Phe II X3	1.07	0.00	1.07	1.07	7
AMD	Phe II X4	1.55	0.00	1.55	1.55	9
	Phe X3	0.98	0.14	0.93	1.33	99
	Phe X4	1.31	0.25	1.29	2.01	151
	Sem	0.70	0.22	0.24	1.08	1099
	Tur 64	1.31	0.20	1.23	1.97	499
	Tur 64 X2	1.78	0.14	1.49	2.03	607
	Atom	0.33	0.02	0.22	0.34	135
	Cel	1.49	0.50	0.26	1.82	2824
	Cel M	1.54	0.43	0.67	1.97	1380
	Cel X2	0.37	0.11	0.34	0.66	25
	Core 2 Duo	2.30	0.17	1.28	2.39	2264
	Core 2 Quad	2.12	0.71	1.69	4.76	370
	Core 2 Solo	2.08	0.00	2.08	2.08	3
Intel	Core Duo	2.37	0.44	1.05	3.08	1251
	Core Solo	2.05	0.14	1.87	2.34	558
	Core i7	4.48	0.02	4.46	4.51	31
	P3	1.56	0.45	0.45	1.62	1002
	P4	1.40	0.38	0.47	1.84	3820
	PD	1.40	0.47	0.61	2.12	790
	PDC	0.55	0.04	0.51	0.62	692
	PM	1.85	0.24	1.53	2.57	2273

We then compute the CPU revenue of each CPU product by multiplying the shipment with the CPU prices. As shown in Table 3.1, AMD's revenue is only 30% of what Intel gains, which is a result of both lower shipment and lower prices.

Figure 3.2: PC Sales-Weighted Average CPU Prices over Time



CPU benchmark is a continuous quality measure of the performance of each CPU model that is collected and published by Passmark.[8] This measure is generated based on users' submission as well as from internal testing.[9] Same as list price, CPU benchmark data is reported at the CPU model level, which allows us to connect the corresponding CPU family name, platform group and CPU speed to each observation. We then match the benchmark data to the sales data from Gartner group based on these three criteria.[10] Table 3.3 offers a summary of the CPU benchmark value across CPU families. AMD's CPUs are on average better than the ones offered by Intel (as Table 3.1 also shows), with more than half of the CPU families enjoying a median quality measure higher than 1000. Only one third of Intel's CPU families are able to reach this threshold.

[8]www.cpubenchmark.net.

[9]PerformanceTest conducts eight different tests and then averages the results to determine the CPU Mark for a system. To ensure that the full CPU power of a PC system is realized, PerformanceTest runs each CPU test on all available CPUs. Specifically, PerformanceTest runs one simultaneous CPU test for every logical CPU (Hyper-threaded); physical CPU core (dual core) or physical CPU package (multiple CPU chips). So hypothetically if you have a PC that has two CPUs, each with dual cores that use hyper-threading then PerformanceTest will run eight simultaneous tests.

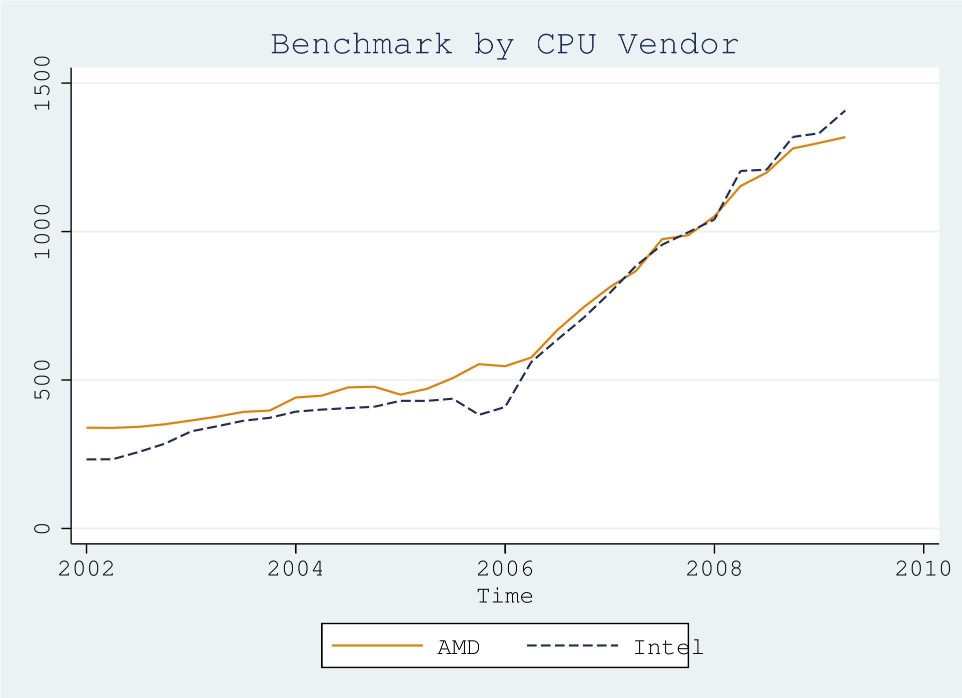
[10]As CPU speed information is limited in Gartner Group's data, this approach is only possible till the first quarter of 2005. After that, we use the help of the list price data to infer which CPU models are marketed in each quarter and match CPU benchmark to Gartner Group's sales data based on CPU family name, year and quarter. Table A.4 and Table A.5 in the appendix present the matched Benchmark on CPU family level in different approaches.

Table 3.3: CPU Benchmark

CPU Firm	CPU Family	Median	Std Dev	Min	Max	Obs
	Ath	4.03	0.42	3.11	4.83	818
	Ath 64	5.86	0.48	4.55	6.98	1151
	Ath 64 X2	13.58	1.66	8.54	15.34	1120
	Dur	3.11	0.34	2.72	3.50	108
	Phe II X3	24.63	0.00	24.63	24.63	7
AMD	Phe II X4	34.99	0.00	34.99	34.99	9
	Phe X3	18.55	0.15	18.31	18.85	99
	Phe X4	25.63	0.72	23.68	25.85	151
	Sem	4.72	0.41	4.11	5.77	1099
	Tur 64	5.09	0.26	4.33	5.09	499
	Tur 64 X2	10.52	0.69	8.94	10.52	607
	Atom	2.99	0.68	2.73	4.74	135
	Cel	3.94	0.99	2.47	6.44	2824
	Cel M	3.67	0.39	2.31	4.33	1380
	Cel X2	12.20	0.00	12.20	12.20	25
	Core 2 Duo	11.21	1.69	11.06	15.80	2264
	Core 2 Quad	37.99	2.67	29.76	38.10	370
	Core 2 Solo	3.20	0.00	3.20	3.20	3
Intel	Core Duo	8.80	0.09	8.53	8.81	1251
	Core Solo	3.84	1.20	3.09	6.86	558
	Core i7	64.54	0.00	64.54	64.54	31
	P3	2.43	0.22	1.96	2.89	1002
	P4	3.57	1.09	1.65	5.37	3820
	PD	8.85	0.29	8.09	9.24	790
	PDC	11.30	2.08	10.32	16.58	692
	PM	3.89	0.37	2.27	4.42	2273

The benchmark scores vary not only across CPU families but also over time within a family. This variation comes from the introduction of new CPU models with higher speed. Figure 3.3 depicts the PC sales-weighted average benchmark scores over time for both CPU vendors. Until the beginning of 2006, AMD offers strictly better CPUs than Intel. Its lead disappears gradually from 2006 on and at the end of our sample periods, Intel seems to gain a technological advantage. Noting that Intel's CPUs are consistently more expensive than those from provided by AMD, a tie in benchmark score implies that AMD's CPUs still have a better quality/price ratio.

Figure 3.3: Sales-Weighted Average Benchmark over Time (CPU Vendor)

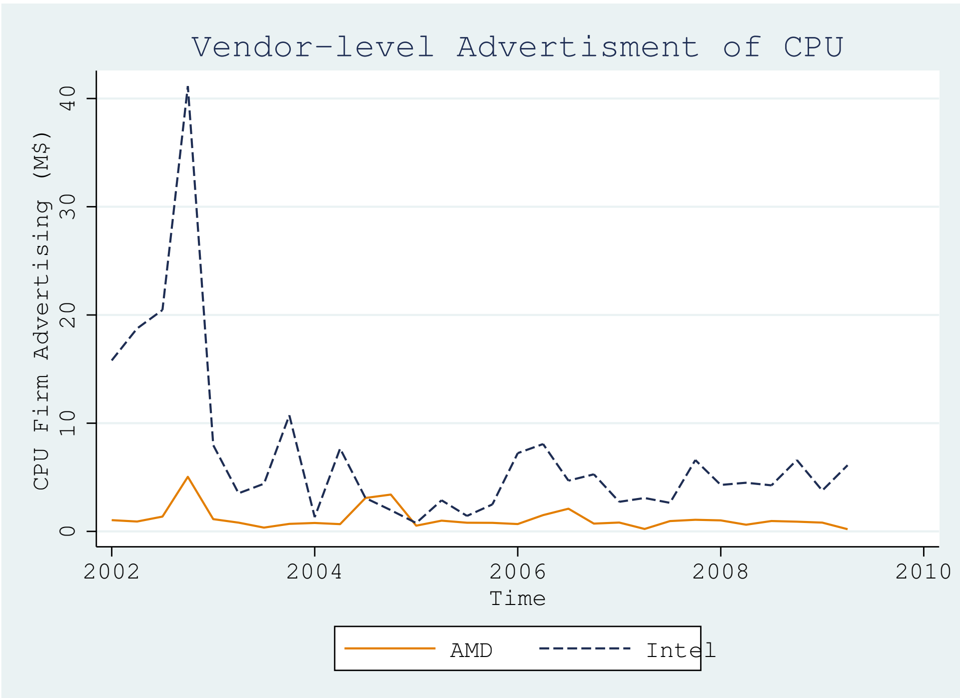


Advertising data consist of PC and CPU advertising expenditures. It provides different levels of advertising: PC firm/CPU vendor level (e.g., Lenovo or Intel), PC brand group/CPU family group level (e.g., Lenovo ThinkPad series or Intel Core series) and PC brand/CPU family level (e.g., Lenovo ThinkPad L412 Notebook or Intel Core i3). We refer the PC firm/CPU vendor level advertising to general promotion, which is beneficial for all PC brands or CPU families. PC firms also advertise non-PC products such as software. We exclude these advertising expenditures. We match this type of advertising to sales data from Gartner Group based on PC firm/CPU vendor, year and quarter. Advertising on the level of PC brand group or CPU family group usually contributes to more than one PC/CPU product. For instance, advertising for *Lenovo Thinkpad – Various Laptop Computers* is allocated to all ThinkPad laptops documented in Gartner Group's data, e.g., ThinkPad G, ThinkPad R, etc. PC brand-specific or CPU family-specific advertisement expenditures are matched to sales data based on brand/family name, platform, year and quarter. For those advertisements that is not platform-specific, we match them only based on brand or brand group. There is also advertisement that faces more than one brand/CPU (e.g. *Lenovo G530 & ThinkPad Notebook Computer : Combo*) or more than one firm (e.g. *Dell Inc & Intel Corp : Combo*). In these cases, we match the advertisement expenditure for both involved parties.

Table 3.1 shows that CPU vendors spent on average 5.2 million dollars on general promotions and 0.7 million dollars for CPU family advertising. Compared to AMD, Intel spent substantially more advertising, with almost 7-times more on vendor-level promotions and double the amount on brand-level advertising than AMD. PC firms spent on average 9.2 million dollars on general promotions and 0.8 million dollars for PC brand advertising. PCs equipped with AMD's CPU have a slightly higher advertisement spending than those with Intel's CPU.

CPU vendor advertising experiences quite big variations over time, especially for Intel. Figure 3.4 illustrates the PC sales-weighted average advertisement expenditure of AMD and Intel over time. Intel advertises consistently more heavily than AMD through out much of the sample periods.

Figure 3.4: Sales-Weighted Average Advertisement Spending on CPU Vendor Level



3.4 Estimation Approach

Our goal is to identify how the advertising affects the revenue of the CPU vendors. We treat a PC firm – PC brand – CPU vendor – CPU family – segment – platform group (e.g. Intel's Pentium M chip that embedded in a deskbased Acer's Aspire N in the business segment) as a CPU product.[11] Our cross-section panel data is then defined as the CPU product over time periods (quarters) from the first quarter of 2002 through the second quarter of 2009.

Our dependent variable is the quarterly total revenue of a CPU family, which is the sum of the quarterly revenue of CPUs that belong to different platform groups (e.g. mobile or desktop) and market in distinct segments (e.g. home, education, etc). The explanatory variables are the quality of the CPU (i.e. the benchmark), the advertisement done by CPU vendors, the advertisement done by PC firms, and the time–consistent characteristics of the CPU product. Those characteristics include the platform group that the CPU is designed for, the segment it is sold in and for which PC firm the CPU is used. The first one helps to control for the unobserved quality or features that is platform–group–specific, the second one captures the unobserved market shock. To further capture the demand environment change over time, we also include a year fixed effect.

Let $TR_{\mathcal{F}_j mt}$ denote the total revenue of CPU family F_j that the CPU product j belongs to, where m is the CPU manufacturer (e.g. Intel or AMD) and t is the time. Notice that the m subscript is redundant, as a CPU is specific to a manufacturer. Our baseline econometric model is given by

$$TR_{\mathcal{F}_j mt} = \alpha x_{mjt} + \beta_1 a^{cpu}_{mjt} + \beta_2 a^{cpu}_{-mt} + \beta_3 a^{pc}_{ljt} + \lambda z_{lj} + \epsilon_{jmt}, \tag{3.1}$$

where x_{mjt} denotes the benchmark of the CPU j, a^{cpu}_{mjt} is the CPU advertisement spending, a^{cpu}_{-mt} is the advertising done by rival CPU vendor $-m$, a^{pc}_{ljt} denotes advertising of PC firm l on PCs with CPU j, and z_{mj} are the set of characteristics that do not change over time, i.e. the platform group, the segment and the PC firm it belongs to. ϵ_{jmt} represents the idiosyncratic error term, which we allow to be correlated within CPU products over time.

We observe various levels of aggregation of advertising expenditures. For a^{cpu}_{mjt}, we include both the CPU vendor–specific advertising $a^{cpu-vendor}_{mt}$, which benefits all the CPU families one vendor has, and CPU family–specific advertising $a^{cpu-family}_{jt}$. Similarly, we use the sum of PC firm–specific and PC brand–specific advertising to form a^{pc}_{ljt}. To compute a^{cpu}_{-mt}, we add up the CPU vendor–specific advertising $a^{cpu-vendor}_{-mt}$ and the sum of all family–specific advertising that is made by vendor $-m$, i.e. $\sum_{k\in -\mathcal{M}_k} a^{cpu-family}_{kt}$, where $-\mathcal{M}_k$ denotes the set of CPU

[11] Ideally, we would also differentiate across different speed groups. However, due to the missing of the cpu speed information from 2005 onward, we aggregate the data to the above mentioned observation level.

families that CPU vendor $-m$ produces. That means, for all the observation j that belongs to the same CPU vendor, they have the same rival advertising variable. This variable is used to capture the competition effects of advertisement.

In order to test whether advertising has long run effect on the consumer's purchase decisions, and thus the revenue of CPUs, we further include the lagged advertisement of CPU up to three quarters in our analysis. Our dynamic econometric model is as following:

$$TR_{\mathcal{F}_j mt} = \alpha x_{mjt} + \beta_1 a^{cpu}_{mjt} + \beta_2 a^{cpu}_{-mt} + \beta_3 a^{pc}_{ljt} + \gamma a^{lag,cpu}_{mjt} + \lambda z_{lj} + \epsilon_{jt}, \tag{3.2}$$

where $a^{lag,cpu}_{mjt}$ denotes the CPU advertising done in the previous periods.

To examine whether Intel use advertising not only for competition purpose but also as a pre-emptive behavior, we test the following three scenarios: (1) we use the subsample that only consists the observation from 2002 to 2005, as this is the period that Intel is suspected by using marketing program to prevent PC firm from using non-Intel chips; (2) we focus on the PC firms that buy exclusively from Intel; (3) we restrict the sample to only CPUs sold to Dell, as the antitrust authorities document the conditional rebates from Intel to Dell.

3.5 Results

3.5.1 Static Baseline

Table 3.4 shows the pooled OLS result based on our static model. Panel (a) presents the result for estimation for Intel CPUs and (b) for AMD CPUs. In the first specification, we only control for the CPU quality and the CPU characteristics that do not change over time. In the second specification, we add own CPU advertising. In the third and fourth specifications, we further controls for rival CPU's advertisement expenditure and advertising of the PC firms, respectively. The last specification include all above mentioned variables.

Despite the different magnitude, the qualitative relation between the revenue and the focal variables – CPU benchmark, CPU advertising, and the adverting done by PC are the same between Intel and AMD. The better the quality of the CPU is, the more revenue a CPU family can gain. Similarly, the higher advertisement spending from both CPU vendor or related PC firms leads to larger revenue. We also confirm the competition effect of rival's advertising, as the coefficient for rival CPU advertising is significantly negative.

CPU benchmark in the last specification has similar effects for Intel and AMD, while the revenue of Intel CPUs is affected much stronger by advertisement. That, to some extent, justify why Intel is more prone to use marketing tool to promote its products than AMD.

Table 3.4: Static Baseline Models

(a) Intel

	(1) CPU Revenue (100M$)	(2) CPU Revenue (100M$)	(3) CPU Revenue (100M$)	(4) CPU Revenue (100M$)	(5) CPU Revenue (100M$)
CPU benchmark (in 1000)	1.126***	0.884***	0.706***	0.675***	0.398*
	(0.268)	(0.256)	(0.248)	(0.245)	(0.231)
Mobile PC	0.509**	0.422*	0.384*	-0.855***	-1.134***
	(0.242)	(0.233)	(0.225)	(0.237)	(0.228)
Own CPU AD (10M$)		2.289***	4.240***	1.760***	4.297***
		(0.0630)	(0.103)	(0.0612)	(0.105)
Rival CPU AD (10M$)			-3.875***		-5.227***
			(0.129)		(0.148)
ADs by PC (10M$)				0.573***	0.675***
				(0.0277)	(0.0286)
Constant	1.383	-4.182**	-6.147***	-8.778***	-12.25***
	(1.686)	(1.655)	(1.624)	(1.547)	(1.482)
year dummies	Yes	Yes	Yes	Yes	Yes
PC Vendor dummies	Yes	Yes	Yes	Yes	Yes
Market dummies	Yes	Yes	Yes	Yes	Yes
Observations	17418	17418	17418	17418	17418
Adjusted R^2	0.082	0.114	0.132	0.154	0.185

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) AMD

	(1) CPU Revenue (100M$)	(2) CPU Revenue (100M$)	(3) CPU Revenue (100M$)	(4) CPU Revenue (100M$)	(5) CPU Revenue (100M$)
CPU benchmark (in 1000)	0.324***	0.321***	0.323***	0.343***	0.347***
	(0.0415)	(0.0412)	(0.0410)	(0.0419)	(0.0417)
Mobile PC	0.109***	0.112***	0.114***	0.114***	0.116***
	(0.0319)	(0.0310)	(0.0311)	(0.0309)	(0.0309)
Own CPU AD (10M$)		0.416***	0.437***	0.280***	0.314***
		(0.0524)	(0.0548)	(0.0516)	(0.0525)
Rival CPU AD (10M$)			-0.0262**		-0.0489***
			(0.0131)		(0.0131)
ADs by PC (10M$)				0.0570***	0.0595***
				(0.00645)	(0.00658)
Constant	1.924***	1.688***	1.743***	1.390***	1.480***
	(0.132)	(0.145)	(0.146)	(0.151)	(0.149)
year dummies	Yes	Yes	Yes	Yes	Yes
PC Vendor dummies	Yes	Yes	Yes	Yes	Yes
Market dummies	Yes	Yes	Yes	Yes	Yes
Observations	5668	5668	5668	5668	5668
Adjusted R^2	0.302	0.315	0.315	0.334	0.336

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.5.2 Dynamics Baseline

We present the estimation result after adding the lags of advertising of own CPU in table 3.6, where the panel (a) shows the result for Intel CPUs and panel (b) for AMD. The first column represent the same specification as the last column in table 3.4. From specification two to specification four, we incorporate advertisement spending lags from $t-1$ period (i.e. the previous quarter) to $t-3$ period, sequentially. The last column denote the specification where we use the cumulative advertising of the three previous quarters as the dynamic control.

All coefficients for the interested variables after controlling for the dynamic effect of advertising remain with the same sign and similar value as in the static specification. We found persistent significant and positive effects of previous advertise spending on the current rev-

Table 3.6: Dynamic Baseline Models

(a) Intel

	(1) CPU Revenue (100M$)	(2) CPU Revenue (100M$)	(3) CPU Revenue (100M$)	(4) CPU Revenue (100M$)	(5) CPU Revenue (100M$)
CPU benchmark (in 1000)	0.398*	0.381*	0.397*	0.463**	0.450**
	(0.231)	(0.225)	(0.223)	(0.222)	(0.221)
Own CPU AD (10M$)	4.297***	4.397***	4.488***	4.618***	4.603***
	(0.105)	(0.118)	(0.115)	(0.111)	(0.113)
Rival CPU AD (10M$)	-5.227***	-6.417***	-6.838***	-7.280***	-7.247***
	(0.148)	(0.166)	(0.164)	(0.165)	(0.163)
ADs by PC (10M$)	0.675***	0.695***	0.684***	0.667***	0.669***
	(0.0286)	(0.0280)	(0.0273)	(0.0260)	(0.0262)
Mobile PC	-1.134***	-1.159***	-1.111***	-1.014***	-1.028***
	(0.228)	(0.222)	(0.218)	(0.215)	(0.215)
Own CPU AD in t-1 (10M$)		1.377***	1.046***	1.067***	
		(0.0439)	(0.0344)	(0.0340)	
Own CPU AD in t-2 (10M$)			1.082***	0.669***	
			(0.0622)	(0.0399)	
Own CPU AD in t-3 (10M$)				1.308***	
				(0.0796)	
Cum. CPU AD (3 quarters)					0.986***
					(0.0415)
Constant	-12.25***	-13.36***	-13.34***	-13.05***	-13.11***
	(1.482)	(1.440)	(1.420)	(1.393)	(1.396)
year dummies	Yes	Yes	Yes	Yes	Yes
PC Vendor dummies	Yes	Yes	Yes	Yes	Yes
Market dummies	Yes	Yes	Yes	Yes	Yes
Observations	17418	17418	17418	17418	17418
Adjusted R^2	0.185	0.208	0.223	0.240	0.238

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) AMD

	(1) CPU Revenue (100M$)	(2) CPU Revenue (100M$)	(3) CPU Revenue (100M$)	(4) CPU Revenue (100M$)	(5) CPU Revenue (100M$)
CPU benchmark (in 1000)	0.347***	0.347***	0.356***	0.369***	0.365***
	(0.0417)	(0.0417)	(0.0415)	(0.0413)	(0.0413)
Own CPU AD (10M$)	0.314***	0.307***	0.358***	0.324***	0.286***
	(0.0525)	(0.0517)	(0.0535)	(0.0537)	(0.0520)
Rival CPU AD (10M$)	-0.0489***	-0.0489***	-0.0554***	-0.0565***	-0.0553***
	(0.0131)	(0.0131)	(0.0127)	(0.0124)	(0.0123)
ADs by PC (10M$)	0.0595***	0.0587***	0.0542***	0.0517***	0.0473***
	(0.00658)	(0.00699)	(0.00686)	(0.00671)	(0.00655)
Mobile PC	0.116***	0.116***	0.122***	0.132***	0.130***
	(0.0309)	(0.0308)	(0.0302)	(0.0296)	(0.0297)
Own CPU AD in t-1 (10M$)		0.0314	-0.0322	0.0739**	
		(0.0336)	(0.0265)	(0.0321)	
Own CPU AD in t-2 (10M$)			0.363***	0.251***	
			(0.0383)	(0.0261)	
Own CPU AD in t-3 (10M$)				0.453***	
				(0.0409)	
Cum. CPU AD (3 quarters)					0.260***
					(0.0297)
Constant	1.480***	1.485***	1.496***	1.519***	1.541***
	(0.149)	(0.148)	(0.146)	(0.145)	(0.146)
year dummies	Yes	Yes	Yes	Yes	Yes
PC Vendor dummies	Yes	Yes	Yes	Yes	Yes
Market dummies	Yes	Yes	Yes	Yes	Yes
Observations	5668	5668	5668	5668	5668
Adjusted R^2	0.336	0.336	0.344	0.356	0.351

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

enue, which confirms our hypothesis that advertising has a long run effect on the consumers.

[12] And this is important to take into account, when we analyze whether Intel is using marketing campaign in an anticompetitive fashion. The advertising lags of Intel show a less strong effect on the revenue than the advertising of current period, while the effects of previous and current advertising are similar for AMD chips.

3.5.3 Subsample of 2002–2005

In this section, we discuss the estimation result obtained from data from year 2002 to the end of year 2005. The first three column of table 3.8 shows the regression of Intel CPU product, with no control for dynamic effect of advertising in the first column and using lags of the previous three quarter separately or forming a cumulative measure in the second and the third columns, respectively. The fourth to sixth columns present the result for CPU products of AMD.

Table 3.8: Revenue with Own and Rival's Advertisement, and PC firm Ad: 2002-2005

	(1) Intel CPU Renevue (100M$)	(2) Intel CPU Renevue (100M$)	(3) Intel CPU Renevue (100M$)	(4) AMD CPU Renevue (100M$)	(5) AMD CPU Renevue (100M$)	(6) AMD CPU Renevue (100M$)
CPU benchmark (in 1000)	-13.04***	-12.00***	-12.09***	0.0600	0.105	0.0899
	(0.581)	(0.571)	(0.580)	(0.0675)	(0.0674)	(0.0689)
Own CPU AD (10M$)	3.405***	3.951***	3.862***	0.611***	0.685***	0.563***
	(0.0757)	(0.0901)	(0.0886)	(0.0689)	(0.0708)	(0.0716)
Rival CPU AD (10M$)	-3.599***	-5.246***	-5.049***	-0.311***	-0.336***	-0.283***
	(0.135)	(0.163)	(0.161)	(0.0301)	(0.0314)	(0.0317)
ADs by PC (10M$)	0.441***	0.470***	0.459***	0.0866***	0.0898***	0.0810***
	(0.0233)	(0.0230)	(0.0224)	(0.00636)	(0.00598)	(0.00636)
Mobile PC	-3.383***	-3.215***	-3.194***	0.0285	0.0393	0.0350
	(0.244)	(0.231)	(0.231)	(0.0547)	(0.0520)	(0.0540)
Own CPU AD in t-1 (10M$)		0.746***			-0.189***	
		(0.0325)			(0.0271)	
Own CPU AD in t-2 (10M$)		0.216***			0.0843***	
		(0.0303)			(0.0166)	
Own CPU AD in t-3 (10M$)		0.551***			0.338***	
		(0.0572)			(0.0374)	
Cum. CPU AD (3 quarters)			0.483***			0.0921***
			(0.0342)			(0.0228)
Constant	0.732	-1.169	-0.771	1.081***	1.129***	1.205***
	(0.763)	(0.761)	(0.754)	(0.174)	(0.172)	(0.173)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
PC Vendor dummies	Yes	Yes	Yes	Yes	Yes	Yes
Market dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7605	7605	7605	1721	1721	1721
Adjusted R^2	0.249	0.297	0.292	0.472	0.497	0.475

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Recall that we find positive and significant effects of CPU quality (i.e. benchmark) on revenue for both Intel and AMD, facing the whole time period from the first quarter of 2002 to the second quarter of 2009. When we restrict the sample to the first three years, the positive effect of quality turns to negative for Intel and vanishes for AMD. That suggests PC firms did not pick the CPU with better quality to install into their PCs. Own CPU advertisement spending of Intel having a smaller effect on the revenue than in our dynamic baseline case

[12]Here, we only control for advertising up to three quarters. Table A.6 shows the specification of including lags up to two years.

indicates that the advertising used by Intel does not translate efficiently into revenue but may be used to defer the entry of AMD.

3.5.4 ED firms

We define ED firms as the PC firms that exclusively use Intel CPUs for all their PCs in that quarter. Table 3.9 shows the estimation result for Intel CPUs that are used by those ED firms. The first three specifications include the whole sample periods, while the last three restrict the time to 2002 – 2005.

Table 3.9: Intel Revenue among ED firms: whole sample and 2002–2005

	(1)	(2)	(3)	(4)	(5)	(6)
				2002-2005	2002-2005	2002-2005
	CPU Renevue (100M$)	CPU Renevue (100M$)	CPU Renevue (100M$)	CPU Renevue (100M$)	CPU Renevue (100M$)	CPU Renevue (100M$)
CPU benchmark (in 1000)	4.410***	4.304***	4.295***	-12.92***	-11.37***	-11.53***
	(1.164)	(1.126)	(1.123)	(1.061)	(1.105)	(1.110)
Own CPU AD (10M$)	3.515***	3.902***	3.887***	3.557***	4.087***	4.019***
	(0.243)	(0.252)	(0.247)	(0.118)	(0.129)	(0.129)
Rival CPU AD (10M$)	-4.004***	-5.600***	-5.521***	-3.548***	-5.116***	-4.946***
	(0.316)	(0.336)	(0.323)	(0.206)	(0.223)	(0.223)
ADs by PC (10M$)	0.458***	0.455***	0.453***	0.337***	0.361***	0.351***
	(0.0336)	(0.0335)	(0.0329)	(0.0288)	(0.0296)	(0.0284)
Mobile PC	-2.261***	-2.003***	-2.012***	-3.479***	-3.239***	-3.232***
	(0.345)	(0.334)	(0.333)	(0.304)	(0.291)	(0.292)
Own CPU AD in t-1 (10M$)		0.819***			0.682***	
		(0.0493)			(0.0447)	
Own CPU AD in t-2 (10M$)		0.357***			0.204***	
		(0.0455)			(0.0437)	
Own CPU AD in t-3 (10M$)		0.855***			0.589***	
		(0.0883)			(0.0834)	
Cum. CPU AD (3 quarters)			0.649***			0.467***
			(0.0489)			(0.0486)
Constant	-3.372	-3.898	-3.785	-1.617	-4.004**	-3.509**
	(2.976)	(2.976)	(2.980)	(1.399)	(1.554)	(1.588)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
PC Vendor dummies	Yes	Yes	Yes	Yes	Yes	Yes
Market dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6083	6083	6083	4047	4047	4047
Adjusted R^2	0.251	0.299	0.297	0.250	0.298	0.294

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

When running regression on the whole time periods, CPU quality turns out to have a positive effect on the revenue. In contrasts, CPU quality affects the revenue negatively in the restricted time periods. That shows the existence of the ED relationship is not necessarily induced by illegal agreement among Intel and those ED firm but the economic incentive. It could be the case that some PC firms choose the better CPUs from Intel that are more compatible with their PCs, and thus leads to higher demand and higher revenue for Intel. However, the negative coefficient of CPU quality in the last three columns suggests that in that problematic period, following the ED agreement is the predominant reason for PC firms to use Intel's CPU exclusively.

3.5.5 Dell

In this section, we focus on one specific ED firm with Intel – Dell. Documents from antitrust authorities suggest that Dell indeed chose to use only CPU from Intel due to Intel's marketing campaign. We show the estimation result in table 3.10. The first panel presents Intel's revenue through selling CPU to Dell and the second panel compares the difference between Intel's and AMD's revenue through Dell from year 2006 onward.[13]

In the first three columns in panel (a), we includes the whole sample periods, while in the last three, we only use the subsample of year 2002 to year 2005. While the Intel's CPU advertising and Dell's advertising have a positive effect on CPU revenue as we discussed in the baseline case, the quality no longer has a positive impact on revenue. The result of the last three columns are quite similar to the ones in the last three columns in table 3.9. That confirms that other ED firms with Intel in year 2002 – 2005 are using Intel's CPU exclusively due to the same reason as Dell, that they have to, rather than choosing it to maximize the profit.

In panal (b), we use the first three columns to show the relation between the Intel's revenue and the interested variables and the last three for AMD. This panel exclude the possibilities that consumers purchasing PCs from Dell does not care about CPU quality or Dell does not care about the CPU quality that it uses. Though the revenue of Intel is not affected by the CPU quality as shown in the first three columns in panel (b), in the last three columns indicate that the revenue of AMD is increasing with benchmark.

[13]As Dell is elusively using Intel's CPU from 2002–2005, in order to have comparable results between AMD and Intel, we only use the time periods that Dell uses CPU from both vendors.

Table 3.10: Revenue from Dell

(a) Intel Revenue from Dell: whole sample and 2002–2005

	(1)	(2)	(3)	(4)	(5)	(6)
				2002-2005	2002-2005	2002-2005
	CPU Renevue (100M$)	CPU Renevue (100M$)	CPU Renevue (100M$)	CPU Renevue (100M$)	CPU Renevue (100M$)	CPU Renevue (100M$)
CPU benchmark (in 1000)	-0.475	-0.382	-0.383	-11.12***	-10.70***	-10.75***
	(0.409)	(0.402)	(0.402)	(1.272)	(1.203)	(1.204)
Own CPU AD (10M$)	4.016***	3.926***	3.937***	3.417***	3.697***	3.648***
	(0.213)	(0.229)	(0.230)	(0.202)	(0.199)	(0.192)
Rival CPU AD (10M$)	-4.672***	-5.356***	-5.319***	-3.356***	-4.351***	-4.215***
	(0.315)	(0.331)	(0.321)	(0.361)	(0.365)	(0.354)
ADs by PC (10M$)	0.623***	0.610***	0.607***	0.379***	0.400***	0.388***
	(0.0692)	(0.0699)	(0.0699)	(0.0578)	(0.0601)	(0.0582)
Mobile PC	-1.833***	-1.577***	-1.578***	-3.675***	-3.323***	-3.323***
	(0.524)	(0.513)	(0.515)	(0.530)	(0.501)	(0.505)
Own CPU AD in t-1 (10M$)		0.782***			0.636***	
		(0.0695)			(0.0740)	
Own CPU AD in t-2 (10M$)		0.504***			0.168**	
		(0.0998)			(0.0852)	
Own CPU AD in t-3 (10M$)		0.734***			0.609***	
		(0.172)			(0.131)	
Cum. CPU AD (3 quarters)			0.657***			0.442***
			(0.0814)			(0.0835)
Constant	-8.749***	-9.354***	-9.304***	-1.508	-2.969***	-2.695**
	(0.893)	(0.862)	(0.852)	(1.160)	(1.115)	(1.077)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Market dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2786	2786	2786	1300	1300	1300
Adjusted R^2	0.165	0.190	0.191	0.266	0.301	0.299

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) Intel and AMD Revenue from Dell: 2006 onward

	(1)	(2)	(3)	(4)	(5)	(6)
	Intel	Intel	Intel	AMD	AMD	AMD
	CPU Renevue (100M$)	CPU Renevue (100M$)	CPU Renevue (100M$)	CPU Renevue (100M$)	CPU Renevue (100M$)	CPU Renevue (100M$)
CPU benchmark (in 1000)	-0.206	-0.233	-0.151	1.294***	1.299***	1.291***
	(0.405)	(0.403)	(0.404)	(0.0493)	(0.0429)	(0.0448)
Own CPU AD (10M$)	3.355***	3.883***	3.381***	0.452	0.687	1.079**
	(0.401)	(0.482)	(0.399)	(0.425)	(0.519)	(0.536)
Rival CPU AD (10M$)	-8.156***	-4.133**	-6.099***	0.0786**	0.00254	0.0680*
	(0.998)	(2.072)	(1.256)	(0.0387)	(0.0385)	(0.0379)
ADs by PC (10M$)	1.284***	1.190***	1.154***	-0.0400***	-0.0368**	-0.0374**
	(0.121)	(0.144)	(0.144)	(0.0149)	(0.0143)	(0.0151)
Mobile PC	-1.307*	-1.246	-1.114	0.132***	0.229***	0.221***
	(0.783)	(0.759)	(0.774)	(0.0482)	(0.0535)	(0.0562)
Own CPU AD in t-1 (10M$)		-0.641**			1.737***	
		(0.283)			(0.341)	
Own CPU AD in t-2 (10M$)		2.340***			0.480**	
		(0.343)			(0.209)	
Own CPU AD in t-3 (10M$)		-0.732			-0.340	
		(1.108)			(0.264)	
Cum. CPU AD (3 quarters)			0.640**			0.602**
			(0.263)			(0.230)
Constant	-6.637***	-7.435***	-6.877***	-0.921***	-1.145***	-1.169***
	(0.918)	(1.010)	(0.902)	(0.147)	(0.108)	(0.113)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Market dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1486	1486	1486	350	350	350
Adjusted R^2	0.200	0.213	0.206	0.658	0.686	0.666

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.6 Robustness Check

The estimation with ED firms employed above use a strict definition of exclusive dealing: zero sales with AMD. In this specification, we classify the PC firm, whose shipment of its PC brands with AMD chips account for less than 10% of its total shipment within a quarter, as a ED firm with Intel. Table 3.12 shows a similar result as in the case where we use the stricter definition.

Table 3.12: Intel Revenue with ED Firms: An Alternative Definition

	(1)	(2)	(3)	(4)	(5)	(6)
				2002-2005	2002-2005	2002-2005
	CPU Renevue (100M$)	CPU Renevue (100M$)	CPU Renevue (100M$)	CPU Renevue (100M$)	CPU Renevue (100M$)	CPU Renevue (100M$)
CPU benchmark (in 1000)	1.198***	1.202***	1.191***	-12.89***	-11.40***	-11.53***
	(0.428)	(0.414)	(0.414)	(1.019)	(1.059)	(1.064)
Own CPU AD (10M$)	4.221***	4.580***	4.572***	3.468***	3.909***	3.838***
	(0.158)	(0.163)	(0.161)	(0.105)	(0.116)	(0.115)
Rival CPU AD (10M$)	-5.088***	-6.827***	-6.793***	-3.489***	-4.841***	-4.671***
	(0.227)	(0.242)	(0.233)	(0.190)	(0.208)	(0.206)
ADs by PC (10M$)	0.656***	0.637***	0.638***	0.374***	0.393***	0.383***
	(0.0372)	(0.0364)	(0.0364)	(0.0282)	(0.0290)	(0.0280)
Mobile PC	-1.373***	-1.179***	-1.194***	-3.582***	-3.363***	-3.351***
	(0.321)	(0.308)	(0.307)	(0.298)	(0.287)	(0.287)
Own CPU AD in t-1 (10M$)		0.962***			0.664***	
		(0.0465)			(0.0411)	
Own CPU AD in t-2 (10M$)		0.497***			0.161***	
		(0.0495)			(0.0430)	
Own CPU AD in t-3 (10M$)		1.193***			0.557***	
		(0.0970)			(0.0735)	
Cum. CPU AD (3 quarters)			0.856***			0.439***
			(0.0509)			(0.0445)
Constant	-12.14***	-12.73***	-12.78***	-1.894	-4.114***	-3.609**
	(1.500)	(1.431)	(1.430)	(1.393)	(1.523)	(1.561)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
PC Vendor dummies	Yes	Yes	Yes	Yes	Yes	Yes
Market dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8973	8973	8973	4532	4532	4532
Adjusted R^2	0.184	0.237	0.234	0.241	0.284	0.280

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.7 Conclusion

In this paper, we investigate the role of advertising in the CPU industry. In particular, we test whether Intel uses advertising as a preemptive tool to weaken its main rival – AMD. We find both CPU manufacturers enjoy a positive return to their revenue from advertisement spending and advertising is not only effective in the current period but also for the future.

In terms of the preemptive effect of advertising, we find supportive evidence both from the data and from the estimation result. Our data shows that from 2002 to 2005, which is the period that Intel is accused of using the marketing campaign illegally, the market share of AMD remained relatively low. After 2005, we observe a dramatic increase in AMD's market share. Our estimation results show that in the problematic period (2002 – 2005) and with the ED firms (e.g., Dell), a CPU with better quality and higher advertisement expenditure does not necessarily lead to a higher profit. That suggests Intel does not only use advertising to be more competitive and more profitable, but rather to use it as a preemptive tool to maintain the dominant position.

A Addendum to Chapter 3

Table A.1: Product Cross-Reference from Processor Core to Brand Name (i.e. Marketing Name) in Sample (Q1:2002 - Q4:2006)

Platform	Type	Processor Core	Brand Name	Speed (Frequency: MHz)
Desktop	Mainstream	Willamette	Pentium 4	1300 - 2000
		Northwood		1600 - 3400
		Prescott		2260 - 3800
		Smithfield*	Pentium D	2667 - 3200
		Presler*		N/A
		Conroe*	Celeron	N/A
			Core 2 Duo	N/A
	Value	Tualatin	Pentium III	1000 - 1400
			Celeron	900 - 1400
		Willamette	Celeron	1500 - 2000
		Northwood		1600 - 2800
		Prescott	Celeron D	2133 - 3460
		Cedar Mill		
		Cedar Mill	Pentium 4	N/A
Mobile	Mainstream	Northwood	Mobile Pentium 4-M	1200 - 2600
		Prescott	Mobile Pentium 4	2300 - 3460
		Banias	Pentium M	1200 - 1800
		Dothan		1300 - 2267
		Yonah*	Core Duo	
	Value	Tualatin	Mobile Celeron	1000 - 1330
			Mobile Pentium III-M	866 - 1333
		Northwood	Mobile Celeron	1400 - 2500
		Banias	Celeron M	1200 - 1500
		Dothan		1200 - 1700
		Yonah		
		Yonah	Core Solo	N/A
	Low-Power	Tualatin LV	Mobile Pentium III-M	733 - 1000
		Tualatin ULV		700 - 933
		Tualatin LV	Mobile Celeron	650 - 1000
		Tualatin ULV		650 - 800
		Banias LV	Pentium M	1100 - 1300
		Banias ULV		900 - 1100
		Dothan LV		1400 - 1600
		Dothan ULV		1000 - 1300
		Banias ULV	Celeron M	600 - 900
		Dothan ULV		900 - 1000
		Yonah ULV		
		Yonah ULV	Core Solo	N/A

Notes: * Dual-core processor

Notes: * Low-power mobile PCs are mini-notebook, tablet, and ultraportables. (LV: low-voltage; ULV: ultra-low-voltage)

Table A.2: Intel CPU Instat Prices by CPU Family in $ from 2002Q1 to 2006Q4

CPU Family	Median	Std Dev	Min	Max	Obs
Cel	153.25	43.71	45.12	185.73	131
Cel M	192.16	43.21	58.81	285.17	143
P3	156.00	43.34	45.12	162.40	40
P4	128.19	43.85	45.12	185.73	127
PD	202.64	54.37	61.51	212.16	12
PM	193.39	23.10	152.07	285.17	129

include both estimated and predicted prices

Table A.3: List Price

CPU Firm	CPU Family	Median	Std Dev	Min	Max	Obs
	Ath	97	67.76	36	588	603
	Ath 64	209	196.00	36	1031	542
	Ath 64 X2	203	220.12	62	1031	309
	Ath X2	74	18.16	56	153	61
	Dur	59	20.16	39	130	56
AMD	Phe II X3	135	11.55	125	145	4
	Phe II X4	195	25.32	175	245	8
	Phe X3	122	23.29	101	195	24
	Phe X4	173	40.95	142	283	43
	Sem	86	25.84	30	145	617
	Tur 64	184	63.04	145	525	246
	Tur 64 X2	220	60.13	154	354	93
	Atom	43	33.21	20	135	234
	Cel	70	24.08	30	134	589
	Cel M	107	32.13	45	161	208
	Cel X2	53	16.35	43	86	107
	Core 2 Duo	284	93.50	113	637	1015
	Core 2 Quad	266	138.41	163	851	381
	Core 2 Solo	262	9.46	241	262	104
Intel	Core Duo	183	123.39	113	706	625
	Core Solo	241	25.38	209	278	51
	Core i3	123	10.54	113	133	10
	Core i5	196	34.18	176	284	44
	Core i7	546	277.42	278	1054	150
	P4	218	185.69	55	999	179
	PD	199	285.17	74	999	89
	PDC	74	8.69	64	87	202
	PM	304	113.52	130	702	409

Table A.4: CPU Benchmark Scores by CPU Family (Gartner Based)

AMD: 2002Q1-2004Q4, Intel: 2002Q1-2005Q3

CPU Firm	CPU Family	Median	Std Dev	Min	Max	Obs
	Ath	376	94.48	183	765	55
AMD	Ath 64	574	84.10	425	682	16
	Dur	272	99.50	243	428	3
	Sem	421	154.09	318	922	20
	Cel	405	387.26	170	1688	64
	Cel M	380	152.47	151	908	22
Intel	P3	265	52.62	195	356	11
	P4	275	147.46	148	688	42
	PD	905	229.60	672	1301	8
	PM	348	107.62	211	596	27

Table A.5: CPU Benchmark Scores by CPU Family (List price Based)

CPU Firm	CPU Family	Median	Std Dev	Min	Max	Obs
	Ath	413	83.82	330	684	56
	Ath 64	579	69.53	425	758	232
	Ath 64 X2	1304	198.84	805	1781	177
	Ath X2	1296	151.26	1036	1603	58
	Phe II X3	2463	133.32	2250	2594	8
AMD	Phe II X4	3435	322.44	3076	4323	23
	Phe X3	1885	155.50	1593	2095	29
	Phe X4	2541	311.51	1941	3047	38
	Sem	460	48.65	362	604	227
	Tur 64	467	62.71	387	616	115
	Tur 64 X2	970	138.40	768	1273	56
	Atom	313	146.18	163	668	56
	Cel	409	302.79	170	1688	363
	Cel M	402	109.33	221	908	123
	Cel X2	1267	80.21	1173	1415	9
	Core 2 Duo	1345	440.94	563	2414	689
	Core 2 Quad	3787	495.11	2976	4606	103
	Core 2 Solo	320	78.76	311	502	23
Intel	Core Duo	880	148.49	537	1144	132
	Core Solo	325	248.20	250	921	37
	Core i3	2763	74.25	2710	2815	2
	Core i5	3111	842.16	1236	4227	14
	Core i7	5692	2055.63	1416	10454	64
	P4	357	152.26	148	688	134
	PD	885	189.61	672	1301	40
	PDC	1264	422.10	711	2504	125
	PM	374	101.54	211	596	102

Table A.6: Revenue Controlling with More Advertisement Lags

(a) Intel

	(1) CPU Revenue (100M$)	(2) CPU Revenue (100M$)	(3) CPU Revenue (100M$)	(4) CPU Revenue (100M$)	(5) CPU Revenue (100M$)	(6) CPU Revenue (100M$)
CPU benchmark (in 1000)	0.546**	0.582***	0.608***	0.659***	0.690***	0.783***
	(0.223)	(0.223)	(0.225)	(0.224)	(0.224)	(0.228)
Own CPU AD (10M$)	4.405***	4.434***	4.312***	4.317***	4.475***	4.036***
	(0.112)	(0.113)	(0.124)	(0.124)	(0.126)	(0.109)
Rival CPU AD (10M$)	-6.995***	-6.921***	-6.789***	-6.912***	-7.139***	-5.912***
	(0.160)	(0.160)	(0.168)	(0.167)	(0.168)	(0.142)
ADs by PC (10M$)	0.682***	0.677***	0.680***	0.711***	0.701***	0.697***
	(0.0258)	(0.0256)	(0.0256)	(0.0256)	(0.0256)	(0.0254)
Mobile PC	-0.993***	-0.952***	-0.937***	-0.928***	-0.859***	-0.808***
	(0.214)	(0.214)	(0.214)	(0.213)	(0.212)	(0.216)
Own CPU AD in t-1 (10M$)	1.121***	1.124***	1.149***	1.087***	1.102***	
	(0.0369)	(0.0353)	(0.0370)	(0.0353)	(0.0357)	
Own CPU AD in t-2 (10M$)	0.648***	0.650***	0.650***	0.763***	0.701***	
	(0.0397)	(0.0399)	(0.0394)	(0.0422)	(0.0408)	
Own CPU AD in t-3 (10M$)	0.996***	0.940***	0.926***	0.891***	0.964***	
	(0.0562)	(0.0541)	(0.0526)	(0.0500)	(0.0521)	
Own CPU AD in t-4 (10M$)	0.948***	0.718***	0.697***	0.657***	0.602***	
	(0.0764)	(0.0636)	(0.0616)	(0.0611)	(0.0579)	
Own CPU AD in t-5 (10M$)		0.505***	0.391***	0.338***	0.372***	
		(0.0509)	(0.0359)	(0.0361)	(0.0374)	
Own CPU AD in t-6 (10M$)			0.287***	-0.157***	-0.218***	
			(0.0647)	(0.0449)	(0.0434)	
Own CPU AD in t-7 (10M$)				1.110***	0.778***	
				(0.0566)	(0.0405)	
Own CPU AD in t-8 (10M$)					0.806***	
					(0.0542)	
Cum. Own CPU AD (2 years)						0.596***
						(0.0325)
Constant	-12.70***	-12.72***	-12.56***	-12.75***	-12.84***	-11.85***
	(1.372)	(1.365)	(1.365)	(1.342)	(1.337)	(1.347)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
PC Vendor dummies	Yes	Yes	Yes	Yes	Yes	Yes
Market dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17418	17418	17418	17418	17418	17418
Adjusted R^2	0.248	0.250	0.251	0.260	0.264	0.252

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) AMD

	(1) CPU Revenue (100M$)	(2) CPU Revenue (100M$)	(3) CPU Revenue (100M$)	(4) CPU Revenue (100M$)	(5) CPU Revenue (100M$)	(6) CPU Revenue (100M$)
CPU benchmark (in 1000)	0.383***	0.393***	0.408***	0.417***	0.421***	0.420***
	(0.0412)	(0.0413)	(0.0416)	(0.0417)	(0.0418)	(0.0417)
Own CPU AD (10M$)	0.328***	0.343***	0.350***	0.336***	0.336***	0.291***
	(0.0539)	(0.0538)	(0.0531)	(0.0536)	(0.0536)	(0.0517)
Rival CPU AD (10M$)	-0.0652***	-0.0584***	-0.0623***	-0.0596***	-0.0598***	-0.0591***
	(0.0126)	(0.0125)	(0.0126)	(0.0125)	(0.0125)	(0.0123)
ADs by PC (10M$)	0.0531***	0.0522***	0.0522***	0.0532***	0.0527***	0.0492***
	(0.00670)	(0.00672)	(0.00673)	(0.00676)	(0.00675)	(0.00626)
Mobile PC	0.139***	0.142***	0.148***	0.151***	0.153***	0.153***
	(0.0292)	(0.0290)	(0.0289)	(0.0289)	(0.0289)	(0.0289)
Own CPU AD in t-1 (10M$)	0.0822**	0.0769**	0.0853**	0.0810**	0.0708**	
	(0.0362)	(0.0347)	(0.0351)	(0.0345)	(0.0336)	
Own CPU AD in t-2 (10M$)	0.323***	0.272***	0.272***	0.266***	0.262***	
	(0.0320)	(0.0290)	(0.0288)	(0.0287)	(0.0286)	
Own CPU AD in t-3 (10M$)	0.334***	0.362***	0.317***	0.313***	0.310***	
	(0.0286)	(0.0299)	(0.0279)	(0.0269)	(0.0268)	
Own CPU AD in t-4 (10M$)	0.385***	0.222***	0.257***	0.217***	0.212***	
	(0.0438)	(0.0322)	(0.0342)	(0.0325)	(0.0324)	
Own CPU AD in t-5 (10M$)		0.381***	0.234***	0.280***	0.269***	
		(0.0427)	(0.0238)	(0.0238)	(0.0227)	
Own CPU AD in t-6 (10M$)			0.385***	0.274***	0.295***	
			(0.0424)	(0.0362)	(0.0351)	
Own CPU AD in t-7 (10M$)				0.281***	0.219***	
				(0.0321)	(0.0260)	
Own CPU AD in t-8 (10M$)					0.150***	
					(0.0314)	
Cum. Own CPU AD (2 years)						0.234***
						(0.0202)
Constant	1.540***	1.532***	1.548***	1.550***	1.558***	1.583***
	(0.144)	(0.143)	(0.143)	(0.143)	(0.143)	(0.144)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
PC Vendor dummies	Yes	Yes	Yes	Yes	Yes	Yes
Market dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5668	5668	5668	5668	5668	5668
Adjusted R^2	0.365	0.372	0.380	0.383	0.384	0.382

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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Curriculum Vitae

Yihan Yan

— 2014–2020	*University of Mannheim* Ph.D. Student in Economics
— 2014–2016	*University of Mannheim* Master in Economics
— 2011–2014	*University of Mannheim* Bachelor in Economics

Ehrenwörtliche Erklärung

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Mannheim, den 17 September 2020

Yihan Yan