Neighborhood Effects in Technology Diffusion: Evidence from the California Electric Vehicle Market

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Abstract

Artificial intelligence, virtual reality, 3D printing, smartphone, internet and the already obsolete household computer... Faster than ever, new technologies are infiltrating every aspect of modern consumers' lives through the process called technology diffusion. This paper studies the role of neighborhood effects in the consumer side of new technology diffusion. Based on a binary choice model, I demonstrate how a consumer's choice of converting to a new technology can be influenced by the general penetration rate of the neighborhood she lives in, and how a community's susceptibility to the neighborhood effect can shape its distinct diffusion process. Through an empirical analysis of the electric vehicle (EV) market in selected counties of California from 2011 to 2015, I verify the existence of neighborhood effects in EV diffusion and find the elasticity of EV demand of a county with respect to its neighbor counties' EV penetration rate is at least 0.78. Moreover, smaller counties are more influenced by their larger neighbors.

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1 Introduction

Throughout history, technology advancement has always been one of the most significant factors improving human productivity. While invention and innovation sometimes come from instantaneous sparks of genius, technology adoption is usually a much longer story. The process by which new technology gradually becomes available to and accepted by a market is called diffusion. Early researchers on R&D tended to believe that adopters and imitators of new technology are necessary to the process, but "somehow unseemly and undeserving" compared to the "heroic" innovators (Silverberg; 1990). From the point of view of social welfare, however, technology diffusion can be as significant as the technology itself: nobody can directly benefit from a commodity which has not even entered the market. Moreover, certain interventions can help optimize the diffusion process. Swift and frictionless adoption of useful technology can greatly boost social productivity and provide sufficient environment for the further development of the technology; likewise, potentially dangerous technologies should better be delayed until sufficient information is collected, to prevent irreversible damages of imprudent adoption. Therefore, better understanding of the diffusion process has important social welfare implications. For this reason, it is of interest for economists to study technological diffusion under various conditions like incomplete information, uncertainty, and individual heterogeneity.

Formal studies focusing on diffusion alone can be traced back to the 1950s (Sarkar; 1998). In one of the classical empirical studies if the topic, Griliches (1957) investigates the adoption of hybrid corn on American farms and successfully identifies the standard "S-shape" diffusion process across states: following slow initial adoption, the fraction of adopters grows increasingly faster until reaching an inflection point, after which diffusion decelerates and eventually reaches a saturation point. Mansfield (1968) tests his theory on innovation and diffusion using data from several major industries, such as iron, steel, petroleum refining, coal and railroad. One common characteristic of these studies is that they focus on the producer side. From a supplier's point of view, selecting between new and old technologies is equivalent to the process of profit maximization, a classical economics area where theories are well developed. Hence, both Griliches and Mansfield develop their models based on the standard producer theory. Also, because many firms record their capital investments and means of production, data collection from industries is easy. For these reasons, most traditional economic analyses of diffusion study technologies that enhance productivity of suppliers. Some of the most discussed areas include agricultural technology adoptions in the past (e.g. Manuelli and Seshadri; 2014) or in some less developed regions (e.g. Luh; 1995), new energy technologies such as the nuclear plant in electricity generation (e.g. Zimmerman; 1982), and environmentally friendly technologies that contains pollution and conserve energy (e.g Jaffe et al.; 1995).

Recently, however, more attention has been shifted to the consumer and residential side of technology adoption. One of the most famous cases is the diffusion of home computer (e.g. Caselli and Coleman; 2001). Researchers also study the diffusion process of mobile phones and their impacts on traditional fixed phones (Liikanen et al.; 2004). As environmentalism becomes more popular among consumers, another area frequently investigated is the diffusion of green products such as hybrid vehicles and LEED registered buildings (Kahn and Vaughn; 2009). This shift in focus is closely related to the change in market structure over the past few decades. Although industrial production technologies are always developing, the most important feature of today's market is the rapid birth of new commodities. From computers to smart phones, technology developments are dense in each modern consumer's life. Not only do managers of large factories make decisions about upgrading machines and tools, but literally everyone ponders the cost and benefit of the latest laptop, an expensive desktop software, or a new car powered by electricity. Therefore, learning about the consumer's side of the diffusion process is equally important.

This study proposes a model of neighborhood effects to understand the consumer side of the new technology diffusion process. Neighborhood effects were first formally introduced as an economic phenomenon by Friedman (1955), who defines them as the uncompensated externality from the action of one individual to the others in the neighborhood. Most traditional studies of neighborhood effects follow Friedman's idea and focus on different spillovers. As economics extends beyond the pure monetary scope, the concept of neighborhood effects start to incorporate "non-economic" factors as well, especially in the context of consumer theory. Compared with the more "shrewd" industrial managers whose only job can be assumed to be profit-maximization, consumers usually do not make decisions solely based on "economic" reasons. For example, many experiments show that psychological factors, such as trust (Berg et al.; 1995), altruism (Andreoni and Miller; 2002) and concern for fairness (Forsythe et al.; 1994), can affect people's decisions and lead to "irrational" behaviors that violate the assumptions of some traditional theories. Also, as humans live in the structure called society, their economic decisions are also inevitably social decisions, which can be influenced by factors like social distance (Akerlof; 1997) and social norms (Elster; 1989). These psychological and social influences are mostly observed when people are exposed to interactions with others, so it is sensible to consider their roles in neighborhood effects.

In the process of technology diffusion, neighborhood effects may be generated by several reasons. First, because of the innovative nature of any new technology, the market tends to have insufficient information about the product. Then, technology adoption of a consumer becomes a decision under uncertainty, with a probability of loss if the technology turns out to be more costly or less efficacious than expected (or a gain if the realization is favorable). The lack of information about the technology would thus hinder a typical risk-averse consumer's adoption, even if the expected returns are in fact positive. Similarly, a completely new technology does not always immediately enter all consumers' sets of choices due to poor advertising, so potential users may be unaware of its presence. In these cases, a reliable source for acquiring information about the technology would be those who have converted. Observing how the technology works for others, consumers can deduce their own value functions through induction. Therefore, the higher rate of concentration a new technology has in a neighborhood, the sooner and better would consumers living there obtain accurate information of it. Neighborhoods effect serve as an information channel to facilitate the spread of effective technologies and filter the unreliable ones.

A closely related source of neighborhood effects is social learning. Like the spread of information, social learning is also about intangible assets of knowledge; however, it focuses more on the accumulation in depth rather than the expansion of coverage. New technology often has a very different method of operation than previous ones, so it takes time for people to learn how to make use of it. Besides the usual learning method such as reading instructions and taking lessons, another major source of knowledge is learning by doing, through which pioneer adopters of a community can create knowledge spillovers for the followers. Once an early user learns something new about the technology, he may teach others through channels like social media and online forums; even if he does not plan to voluntarily help others, interested potential adopters who live in a close geographical neighborhood with the person can observe his behaviors and then acquire the knowledge. When more experiences are generated and more people join the market, the social capital of knowledge grows, adding value to the technology itself; this would further attract more consumers. Hence, the utility generated by the same technology can be positively correlated with the number of existing users inside the neighborhood and with the total time that they have used it.

Social pressure can also affect the adoption decisions of consumers. The influence of society on individual consumer's decisions has been frequently studied by sociologists and economists. In our case, for the purpose of "conformity", a consumer initially not interested in a new technology might be "forced" to adopt it simply because a large proportion, or even the majority, of the neighborhood he lives in has adopted. If the new technology is designed to fulfill a socially welcomed idea, such as the green products to environmental protection, saliency can be a decision factor as well. Besides, increasing adoption can form fashions or trends which would change a bystander's taste for the technology. On the other hand, the reverse side of these effects is also possible: solid rejection of a technology by a community can discourage the adoption of an individual member who could otherwise benefit much from it herself. Although the social pressure models are sometimes criticized by some economists for "a lack of economic incentives" in their explanations (Young; 2009), these effects are intuitively sensible as a natural pattern of human thinking; many studies also capture different levels of social influences, so they are likely to play a role in the neighborhood effect.

For testing the theory, an empirical case study that identifies and estimates neighborhood effects of technology diffusion in the real world is necessary. This paper considers the expansion of the electric vehicle (EV) market in California. More specifically, I estimate the effect on a county's EV demand by its neighborhood's EV adoption situation. Because a consumer's utility of EV will be a function of the conversion rate in the geographical neighborhood surrounding her, I postulate that any external demand shock would affect the neighborhood with higher pre-existing penetration rate more. While a county's own penetration rate might be the more natural choice to measure the direct neighborhood effect, such stock variables are inherently correlated with other omitted variables which will bias any OLS regression. As a result, I turn to the adoption rate of all other neighbor counties inside the same Metropolitan Statistical Area (MSA). Under the assumption that neighborhood effects are reflexive and not confined within any specific boundary, I can extrapolate the general level of the effect from the "indirect" neighborhood effect estimated. To proxy for a county's demand for EV, I use the EV rebate application data from the Clean Vehicle Rebate Program (CVRP), an official program by the California state government to provide rebate dollars to all eligible EV consumers. Since many counties in California do not belong to any MSA or are the only counties in their MSAs, only 20 counties out of the 58 counties have "neighbors" by my definition. Also, in order to use the log specification, I restrict entities to counties with nonzero applications in all quarters from 2011 to 2015. By the end, 15 counties from 5 MSAs are selected to form a panel of the quarterly county-level EV demand.

While a simple OLS regression of a county's EV demand on its neighbor counties' average penetration rate might be the most straightforward method, endogeneity issues of various levels will unfortunately bias our estimation. To deal with the potential omitted variables, I include county-level demographic characteristics and fixed effects as controls. To solve the reflection problem whereby a county's current demand its neighbors' adoption rates are mutually functions of each other, I use the instrumental variable of neighbor counties' "high-EV-demand household rate", which is defined as the percentage of households with at least two members and exactly one vehicle, to estimate the neighborhood penetration rate in the first stage. The intuition is based on a major technological shortage of current EV models: due to the battery capacity limit and the undeveloped public EV charging station network, most EVs are not yet suitable for long-range traveling; hence, households without any vehicle are not likely to purchase an EV as their first vehicle. Since the demographic variables are fixed values, they are interacted with the state-level EV adoption rates to reflect the disproportionate effects of demand shocks.

After dealing with the endogeneity between the stock and flow variables, I estimate a positive correlation between a county's current demand of EV and the EV penetration rate in its neighbor counties: for every 10% increase in the neighborhood cumulative rebate applications, the current period number of applications increases by 7.8%. In other words, the elasticity of EV demand with respect to neighborhood EV penetration rate is 0.78. This result provides evidence of neighborhood effects in technology diffusion. Also, for the control variables, I find that the high school attainment rate of a county has a negative relationship with its EV demand. This could suggest that contrary to the popular impression that people with good educations are more concerned about environment, the "less" educated population might in fact have a higher demand for EV, a green product. By including an interaction term between the neighbor counties' penetration rate and the relative size of the county itself, I observe that larger counties tend to be less influenced by neighbors, while small counties are more susceptible. This result supports the hypothesis of heterogeneous neighborhood effects among different communities.

The rest of the paper is organized as follows. Section 2 begins with a simple theoretical model of technology diffusion based on the discrete choice model. Section 3 presents the background introduction of the electric vehicles and the EV market, particularly in California. Section 4 describes the empirical framework and presents the result of regression. At last, Section 5 briefly concludes with caveat discussions and future thoughts.

2 Theoretical Basis

Neighborhood effects have always been considered an important factor in consumer theory. Brock and Durlauf (2001) uses a discrete choice framework to capture the influence of social interactions on individual decision making. One key characteristics of this neighborhood effect model is that under some assumptions of the population distribution, the decision mechanism can be reduced to either the logistic function or the CDF of normal distribution, both whose shapes agree well with the standard "S-shape" adoption curve found by most empirical studies of technology diffusion. Moreover, while Brock and Durlauf's model emphasizes people's subjective expectations over average decisions in the community they live in, the main methodology can be easily adapted when future expectation is replaced by de facto realization (Zeppini; 2015). As a result, neighborhood effects become a natural candidate to explain the source of diffusion. Neighborhood effects are also observed empirically in technology diffusion processes, such as in the spread of home computers (Goolsbee and Klenow; 2002) and the penetration of agricultural technology into pineapple cultivations in Ghana (Conley and Udry; 2010).

I consider a variant of Brock and Durlauf's discrete choice model to incorporate the cumulative neighborhood penetration rate of a new technology into an individual consumer's current adoption decision making process. The spirit of this model is similar to Zeppini's; however, as this paper seeks to shed some light on how neighborhood effects shape the diffusion process and its welfare implications in the real world, I focus more on positive predictions than on normative analysis of equilibria conditions. Moreover, I consider not only neighborhood effects within a homogeneous population, but also the interactions among different groups with heterogeneous neighborhood susceptibilities. Based on the assumption that groups within a same geographical community respond to the same neighborhood effect disproportionately, I discuss the influence of differentiated subsidiary policies on the overall rate of adoption.

2.1 Model Setup

First, consider the simple binary choice model for a group I with time invariant preference characteristics and fixed population. Suppose that at first, there is only one conventional technology A used by everyone in the group. Starting from time t_0, a new technology, B, is introduced into the market as a close substitute to A. Now, with two options at hand, every consumer $i \in I$ must choose one technology $j \in \{A, B\}$ based on her utility function which consists of the deterministic values of the technology, personal preferences and neighborhood effects. For the purpose of simplicity, assume that there is no fixed cost of switching between technologies, but the two technologies may have different operation costs. Then, the indirect utility functions can be summarized as

$$V_{ijt} = \lambda_j + \gamma_j P_j(t-1) + \varepsilon_{ij}. \tag{1}$$

For each technology j, λ_j denotes the deterministic characteristics of the product received identically by each consumer. Assume for now that there is no technological progression and that this parameter is constant across time. $P_j(t-1)$ is the lagged average adoption rate of the technology by the group at time t, so it reflects the basis for neighborhood effects. γ_j is the linear coefficient for the effects. While the first two terms are homogeneous within the population, ε_{ij} is consumer i's personal preference over j not captured by the economist. For the purpose of modeling, we assume that for each j, $\{\varepsilon_{ij} : i \in I\}$ are *i.i.d* extreme value distributions. Now, the consumer faces a standard discrete choice problem, and she would convert to the new technology if and only if $V_{iBt} \geqslant V_{iAt}$. Because $\varepsilon_i j$ is a random variable as well as the only term that varies across individuals, any consumer would choose the new technology with the probability

$$\begin{aligned} P(V_{iAt} \leqslant V_{iBt}) &= P(\varepsilon_{iA} - \varepsilon_{iB} \leqslant \lambda_B - \lambda_A + \gamma_B P_B(t-1) - \gamma_A P_A(t-1)) \\ &= P(\varepsilon_i \leqslant (\lambda_B - \lambda_A) + (\gamma_B + \gamma_A) P_B(t-1) - \gamma_A) \end{aligned} \tag{2}$$

The second equation comes from setting $\varepsilon_i \equiv \varepsilon_{iA} - \varepsilon_{iB}$ and from the condition that when there are only two technologies available, $P_A(t) = 1 - P_B(t)$. Suppose for simplicity that the returns to neighborhood effects are the same across the two technologies, as denoted by γ. Let λ be the difference between λ_B and λ_A to reflect the characteristic advantage (disadvantage) of the new technology when it is positive (negative). Two facts may help us precede: first, the difference of two extreme values is known to be distributed logistic; second, the expected fraction of people choosing B, which is also its market share, equals the average adoption probability for each individual. Thus, let $P_B(t)$ be the expected market share of the new technology at t; we will have

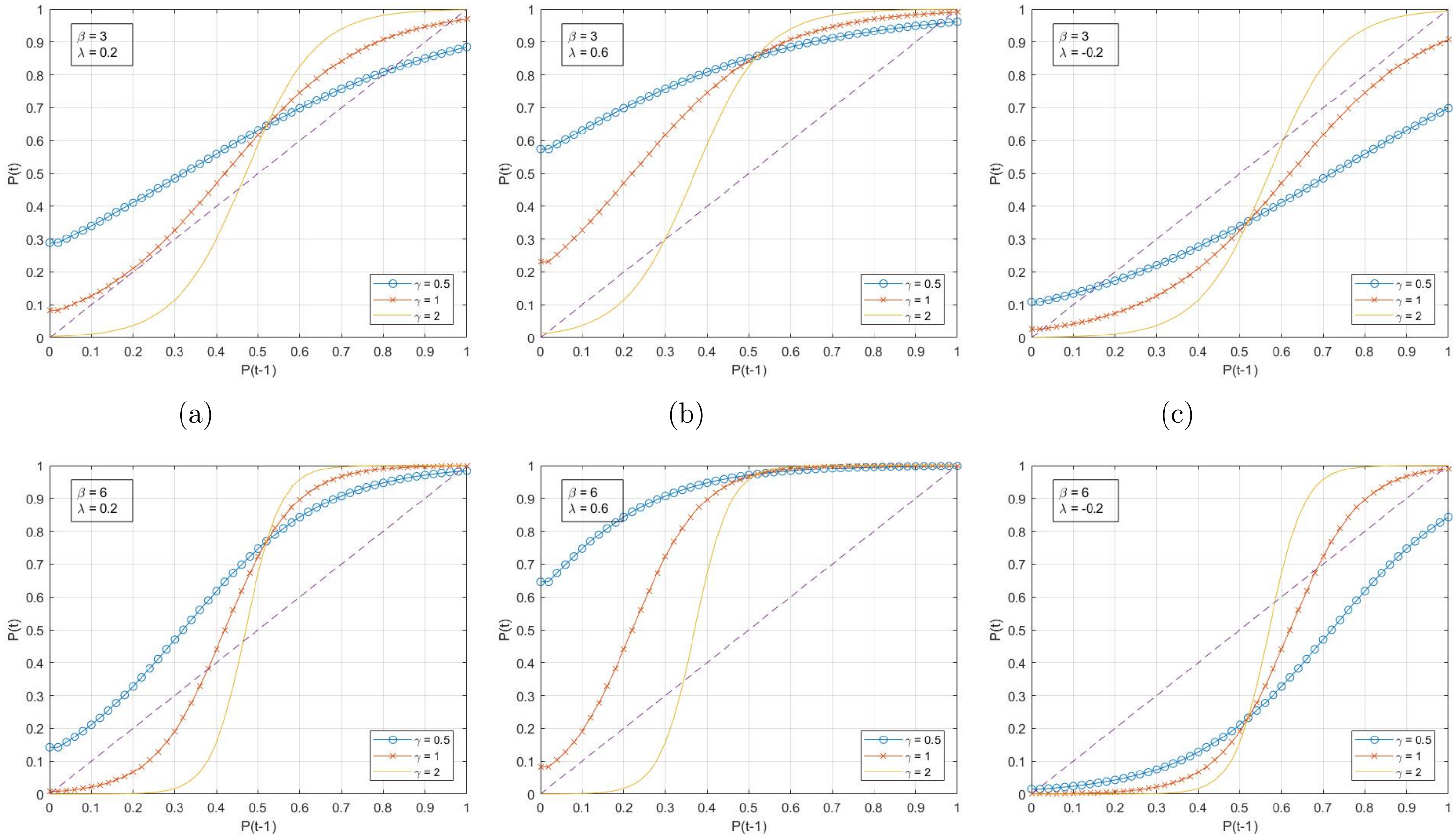
$$P_B(t) = \frac{1}{1 + e^{-\beta[\lambda + \gamma(2P_B(t-1)-1)]}}. \tag{3}$$

Here, β is a parameter inversely related to the variance of ε_i and restricted to be positive; it measures the density of choice within the group (Hommes; 2006). As $\beta \to \infty$, the individual preferences become squeezed into a "rational zone", and each consumer would choose whichever technology yields higher characteristic payoff. On the other hand, when β goes to 0, individual preferences become so diverse that no matter how efficient a technology is, half of the population always prefers the other kind (i.e. $P_B(t) \to 0.5$).[1]

Before adding more conditions to make the model more realistic, let's consider some comparative statics with this simple specification. Since our interest is the effect of neighborhood, we shall restrict the main analysis with respect to γ. Figure 1 shows one period mappings from $P_B(t-1)$ to $P_B(t)$ when we change γ under different sets of fixed β and λ. Subscript of B is dropped for conciseness whenever there is no confusion. Subfigures in the same row have the same density of choice parameter β, and those in the same column have the same characteristics difference parameter λ. Note that an unstable equilibrium is generated at which the graph of the function crosses with the 45 degree dash line representing $P(t) = P(t-1)$ from below, while a stable one happens when the graph crosses from above. Also, by our simple construction, the three graphs in each figure should intersect exactly at the point $P(t-1) = 0.5$, where the two technologies have the same market share so neighborhood effects cancel. The slight graphical inaccuracy that some curves intersect at a point near 0.5 is due to approximation imprecision.

We notice a general pattern that the graphs with higher γ, which represent the adoption decisions of the groups being more sensitive to neighbors' behaviors (we would refer to them as the high-types), start with lower positions on the left side in each of the six figures. Since the function represents the adoption dynamics in each period, it means that the more socially susceptible groups would quickly switch back to the old technology even if any external shocks temporarily push up the adoption rates by a little. Neighborhood effect could help explain the phenomenon in various ways. From the perspective of social pressure, a strong social norm "punishing" any innovators who "break the rule" would suppress diffusion of small scale. On the other hand, in a group highly relying on social learning, consumers who "inadvertently" convert to the new technology might soon be discouraged by the lack of fellow adopters, and thus turn back to the conventional technology. As the independent variable increases, however, the graphs of the high-types move upward rapidly and would

[1] For more details on this and other analytical results of the model, see Zeppini (2015).



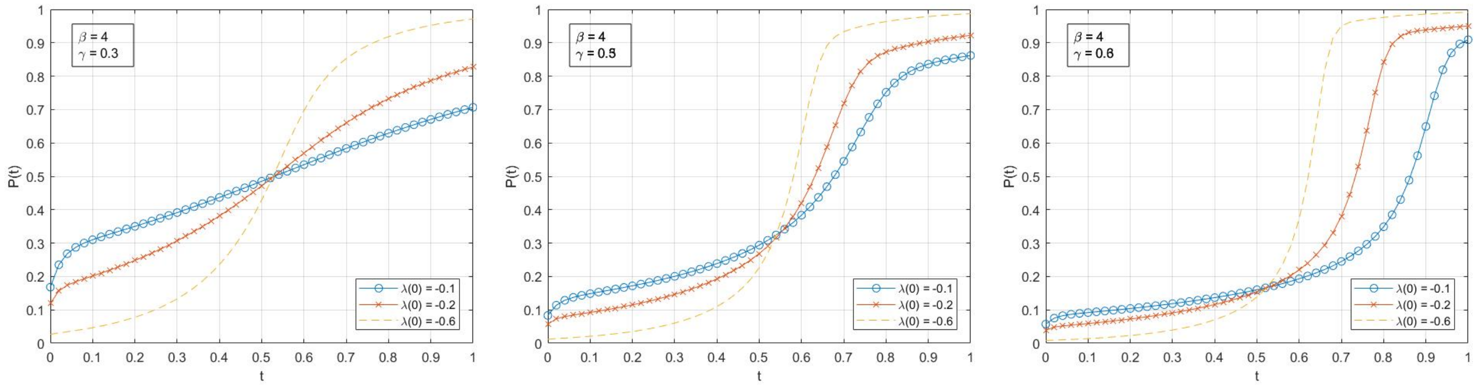
(a) (b) (c)

(d) (e) (f)

Figure 1: Comparative statics.

eventually exceed the lower γ types after the intersection point. They also converge to the highest stable equilibria at $P(t-1) = 1$. Although under the "gravity" of old technology, the high groups will not voluntarily start to convert, diffusion processes might still be triggered by a large enough exogeneous demand shock. For instance, suppose the government of the $\gamma = 2$ group in (a) decides to give the new technology products for free to half of the population; then the adoption rate will be instantaneously raised to 0.5 and the diffusion will continue rapidly. This pattern reflects an important attribute of the high γ type members: because their utilities are so much influenced by the adoption decisions of others, they tend to "agree" with others at any time; hence, it is very hard for the new technology to penetrate the group at first, but once a threshold level is met, the strong momentum makes the residual diffusion almost effortless.

Next, we compare the figures horizontally and vertically to consider how characteristics difference between the two technologies and how individual preference homogeneity can affect the adoption behaviors of different types. When the new technology is indeed superior, e.g. in (a) and (b), uniform conversion is the Pareto efficient equilibrium for the majority of any community because more people can enjoy the benefits of the technology upgrade. Note that some "stubborn" or "nostalgic" consumers who refuse to convert despite a large positive λ always exist under the assumption of the extreme value distribution, as long as β is finite or the variance of ε_i is positive. For a fixed λ, the proportion of such population is inversely related to the homogeneity of the group (e.g., compare (a) and (d)), and is less than a half. Hence, an advantageous new technology would benefit the majority if the second equilibrium



(a) (b) (c)

Figure 2: Cumulative diffusion curves.

is chosen, provided that it exists. Moreover, following the previous analysis, we know that the high-types always either enjoy higher stable points near $P(t-1) = 1$, so even more people can benefit from the technology in a high-type community than a low-type. On the other hand, if the new technology has a net disadvantage, the comparison is reversed as the lower equilibrium will be more efficient for most people. In this case, a low-type group might not start to convert at all (e.g. see $\gamma = 0.5$ in (c) or (f)), but the high-type might converge to the higher equilibrium if an exogenous shock pushes the adoption rate beyond the threshold. Then, the high γ changes from a "premium" into a "penalty", in the sense that it "forces" people to cluster at a less efficient outcome.

The current model is useful for comparative static analysis, but not so to model most diffusion processes in the real world. Because we assume that all characteristics of the consumers and the products are fixed throughout time, the "destiny" of an entering technology is also predestined: typically, it either rapidly dominates the market or does not diffuse at all. Neither case is close to the "S-shape" curve that we usually observe. To make the model a little more realistic, consider a linear technological development for the new technology after it is first available at $t = 0$. At the same time, the old technology remains constant throughout the process. This is equivalent to $\frac{\partial \lambda_t}{\partial t} = c > 0$. More specifically, the new technology starts with technological disadvantages of $\lambda_0 = -\frac{c}{2}$, but catches up with the old technology ($\lambda_{\frac{1}{2}} = 0$) and eventually reverses the situation at the end ($\lambda_1 = \frac{c}{2}$). Figure 2 plots the cumulative diffusion curves of different initial technology statuses. Time is normalized to be 50 periods. Despite the linear technology progression, we observe nonlinear trends of diffusion close to the "S-shape" curve due to the logistic function. From (a) to (c), as γ increases with other parameters fixed, the curve becomes steeper in the middle and flatter at both ends, suggesting that the high-types are more "cautious" or less "sensitive" to the initial catch-up but would swiftly "rush" to the front once the new technology does become superior. Other results are similar to our previous one-period mapping analysis.

2.2 Policy Simulation

Now, on top of the technological progression, consider a slight further modification to the model. Suppose that:

1) Instead of one group only, there are two groups of consumers, I_1 and I_2, in a same

community. Both groups share the same size and the same deterministic payoff of the two products, but have different susceptibilities to the average diffusion rate of the whole community. Such a difference could result from the cultural aspects of the two groups, the geographical structure of neighborhoods, and other demographic attributes.

2) In order to accelerate the new technology diffusion when it is at comparative disadvantage, the manufacturer of the product or the government implements a promotional policy which rewards the consumers who choose B with a subsidy. The effect of subsidy directly enters the consumers' indirect utility functions. To allow for differentiated policies, the amounts of subsidies in group 1 and 2 at time t are denoted as $s_{1,t}$ and $s_{2,t}$.

With these new assumptions, the diffusion rate for I_1 becomes

$$P_1(t, s_1) = \frac{1}{1 + e^{-\beta[(\lambda_t)+s_1+\gamma_1(P_1(t-1)+P_2(t-1)-1)]}}. \tag{4}$$

A similar equation applies for $P_2(t, s_2)$ with γ_1 replaced by γ_2. Suppose that at any given time, the policy maker can readjust the subsidy for both groups; also, her only objective is to maximize the average short-term diffusion rate of the current period given her budget, so t can be taken as a constant. After the budget constraint is normalized by the equal population of the two groups, her problem can be written as

$$\arg\max_{s_1,s_2} P_t(s_1, s_2) \equiv \arg\max_{s_1,s_2} P_{1,t}(s_1) + P_{2,t}(s_2)$$

subject to

$$s_1 P_{1,t}(s_1) + s_2 P_{2,t}(s_2) = M.$$

Technically, this kind of subsidy should be one-time, so it is more precise to represent the spending as the multiplication of subsidy amount and newly converted population, instead of the cumulative adopters. However, since we assume that consumers make decisions in every period and that there is no fixed cost, the model is incapable of capturing one-time subsidy. On the other hand, it is possible to think of the subsidies here as persistent rewards, such as tax cuts for owning the new technology or special offers for some operation costs. In this way, we can proceed to solve the problem. The first order condition gives that at each time period, the optimal levels of s_1 and s_2 should have

$$\frac{dP_1}{ds_1}\left(\frac{dP_2}{ds_2}s_2 + P_2\right) = \frac{dP_2}{ds_2}\left(\frac{dP_1}{ds_1}s_1 + P_1\right). \tag{5}$$

All mathematical details can be found for this section can be found in the appendix. Let $P \equiv \frac{1}{2}(P_{1,t-1} + P_{2,t-1})$ be the average adoption rate of the community in last period, which is also a constant. Some simplifications and substitutions lead us to

$$\begin{aligned} s_2 - s_1 &= \frac{P_1}{dP_1/ds_1} - \frac{P_2}{dP_2/ds_2} \\ &= \frac{e^{\beta\lambda}}{\beta}[\exp\bigl(\gamma_1(2P-1)+s_1\bigr) - \exp\bigl(\gamma_2(2P-1)+s_2\bigr)]. \end{aligned} \tag{6}$$

Without indulging too much into algebra and solving for optimal levels, we shall briefly analyze the maximization condition of s_1 and s_2. Assume that group 1 receives higher effect from the neighborhood, so $\gamma_1 > \gamma_2$. From equation (4) and previous analysis, we know that at the initial stages of diffusion when the new technology is at disadvantage, P is certainly less than a half (otherwise there is probably no need for subsidy at all); then extra sensitivity to neighborhood induces a negative effect to the adoption rate within the high-type group. This is reflected in (6) by $\gamma_1(2P-1) < \gamma_2(2P-1)$. Suppose that $s_1 < s_2$; then the right-hand-side of (6) would be negative, suggesting that $s_2 - s_1 < 0$, which is clearly a contradiction. Hence, before the average diffusion rate of the community reaches 0.5, the optimal promotional policy would always be $s_1 > s_2$, or to subsidize the high-type group more. The intuition is that because adoption rate of group 1 is more negatively influenced by the neighborhood effect of the old technology, by raising its subsidy, policy maker can neutralize and balance the marginal effects across the two groups, thus maximizing the short-term average adoption rate. We also now that positive solutions for s_1, s_2 always exist because when $s_2 - s_1$ in (6) is moved to the right-hand-side, each term is continuous and the whole function reaches both negative (e.g. take any $0 < s_1 < s_2$) and positive (e.g. let $s_1 = \gamma_1(1-2P) > \gamma_2(1-2P) = s_2$) values. A necessary condition for the optimal solutions is

$$0 \leqslant s_1 - s_2 \leqslant (\gamma_1 - \gamma_2)(1 - 2P). \tag{7}$$

When $\gamma_1 - \gamma_2$ or $1 - 2P$ tend to 0 from positive, either the two groups are not significantly different in susceptibilities to the neighborhood effect or the new technology has a market share close to a half; then, there will be no more reason to further adopt the differentiated subsidiary policies. Similar analysis can be applied to cases where P exceeds 0.5 and most results will be reversed, but usually subsidy ends much before that ever happens so we skip the discussion.

We now have two major predictions from the theoretical model: a group's current demand of a new technology would be influenced by the cumulative adoption rate of its neighborhood; groups with distinct susceptibilities to the neighborhood effect from a same geographical region respond differently to promotional policies. To test the theory, I conduct an empirical analysis based on the electric vehicle (EV) market in selected counties in California. The results are mixed. In short, neighbors are indeed identified to have positive influence on the average county-level EV demand, but due to the lack of more specific personal-level data, this research is unable to further distinguish the values of γ parameter within each community. Also, the effects of subsidy policies are not tested because of difficulties in controlling for price factors. Before formally describing the empirical strategy, I will give a brief introduction to the EV market and explain my incentives to focus on it.

3 Electric Vehicle Market

To most people just a few years ago, plug-in electric vehicles (PEV), automobiles that can be charged from external source of electricity such as the electric grid, were merely a concept, a symbol of science fiction, or at most, luxuries for the rich only. Nonetheless, nowadays, electrification of vehicles is widely considered as a foreseeable revolution to the automotive industry all over the world. Developed countries like the United Kingdom, Norway and France have set goals to end gas and diesel car sales by as early as 2025 or 2040. The largest developing country, China, is also the largest market for electric cars. From traditional giants like Toyota and Ford to the new stars like Tesla and BYD, automotive manufacturers sold more than 750,000 EVs in 2016, and are expecting the number to climb steadily in the future. In 2011, President Barack Obama announced the goal of reaching 1 million EV sales in America by 2015. Though the statement was soon realized to be more ambitious than realistic, the United States government does take multidimensional approaches to support the industry, including grants to battery makers and auto producers, investment in R&D, infrastructure construction, as well as tax credits to consumers. In 2016, cumulative EV sales in America totaled about 570,000[2].

Most electric vehicles in today's market can be classified as either battery electric vehicles (BEV), which are completely powered by electricity stored in the battery, or plug-in hybrid electric vehicles (PHEV), which have a smaller battery as well as a traditional gasoline engine. Compared with pure gasoline and diesel cars, EVs, when powered by electricity stored in batteries, do not produce greenhouse gas emissions (except PHEV in its hybrid mode). As a result, in some places, EV is also called zero-emission vehicle (ZEV)[3]. It should be noted that the term "zero-emission" is not necessarily accurate, however, if the electricity is not from clean energy. For example, in 2016, 64.2 percent of electricity generated in the United States comes from burning coal or natural gas, both of which are also major sources of greenhouse gas. Although EV does help ease air pollution in metropolitan areas where the density of cars is high and help reduce greenhouse gas emissions on average, it is also believed to "shift" pollution to relatively remote places where power plants are located, and increase some other pollutants not so common in gasoline waste as in coal-burning waste. For instance, researchers find that a uniform federal subsidy of $7,500 alone provides positive social returns in places with clean electricity sources and high vehicle concentration rates such as California, but across states the returns are -$1,095 on average (Holland et al.; 2016).

Even with these controversies, EV is by far the most promising way known to solve the automotive tailpipe pollution problem; both governments and major producers have heavily invested in the prospect of EV diffusion. However, the still immature technology has several disadvantages compared to conventional gasoline engine vehicles, which largely limit its current penetration. First, although the low electricity price gives EV low operation costs, the purchase cost is considerably higher than most conventional cars, primarily due to the expensive large battery. Columns 1-4 in Table 1 list the price comparison across vehicles of roughly the same models and from the same manufacturers but with different fuel types in the US market. Take the 2018 Ford Fusion as an example. The gasoline powered 2018 Fusion has a manufacturer suggested retail price (MSRP) of $23,395, but the PHEV version has a price of $31,305, despite of its relatively small battery. The 2018 Chevrolet Bolt, a BEV with a much larger battery, costs more than two times as much as the Cruze, its gasoline counterpart. Also, most potential EV users are concerned with the range problem of EV. Typically, in 2017, a fully charged BEV has a maximum range of only 100-200 miles until it runs out of battery (see Column 6); recharging EV is another problem, since public charging stations are far from as convenient and common as gasoline stations, and

[2]Sales data and government agenda acquired from International Energy Agency (IEA), Global EV Outlook 2017 (https:// www.iea.org/publications/ freepublications/publication/ GlobalEVOutlook 2017.pdf).

[3]According to the definition by California Air Resources Board, ZEVs include plug-in electric vehicles (PEV) and fuel cell electric vehicles (FCEV); the latter group is omitted from discussion, and from any other cases when ZEV is referred to because of its different nature and its current unpopularity.

charging usually takes hours. Together these two shortages make long-range trips with EV mostly impossible and put consumers at risk of breaking down on the road. PHEV partially solve these concerns because the gasoline engine is always there as back up, yet it is only a compromised solution which sacrifices the electricity range; Direct Current (DC) fast charge is a technology that could substantially reduce charging time, but its high deployment cost makes it still unavailable in most areas.

Table 1: Vehicles Comparison

Make	**Model***	**Type**	**MSRP ($)**	**MPG/MPGe***	**Battery Range**
Ford	Focus	Gasoline	17,860	28	N/A
Ford	Focus	BEV	29,120	107	115
Ford	Fusion	Gasoline	23,395	25	N/A
Ford	Fusion	Hybrid	26,245	42	N/A
Ford	Fusion	PHEV	31,305	97	21
Chevrolet	Cruze	Gasoline	16,975	31	N/A
Chevrolet	Bolt	BEV	37,495	119	238
Chevrolet	Volt	PHEV	34,095	106	53
Chevrolet	Malibu	Gasoline	21,680	26	N/A
Chevrolet	Malibu	Hybrid	27,920	46	N/A
Toyota	Prius	Hybrid	23,475	52	N/A
Toyota	Prius	PHEV	27,100	133	25
Nissan	Sentra	Gasoline	16,990	30	N/A
Nissan	Leaf	BEV	29,990	112	150

*: Models listed are all in 2018, except Toyota Prius PHEV in 2017.

**: Miles Per Gallon for gasoline/hybrid models; MPG-equivalent for BEV/PHEV models under battery mode.

Sources: manufacturers' websites.

Figure 3 illustrates the price disadvantage of EV even when discounts and fuel costs are considered. The graph is generated by the Alternative Fuels Data Center (AFDC). The horizontal axis is the number of years after purchasing and the vertical axis is the inflation discounted cumulative total cost, assuming a five-year loan with a 10% down payment, 3$ per gallon gasoline price, standard California electricity price and 35 miles daily driving distance with 50% on the highway. Notice that in the first 5 years, the costs of EV are higher than the gasoline engine car because of the high purchasing price; EV's lower operation costs do shrink the gap, but even in the long-run of 15 years the total costs of EV are still much higher. While technology advancement keeps improving on these shortcomings, they are still barriers to a typical consumer's EV adoption.

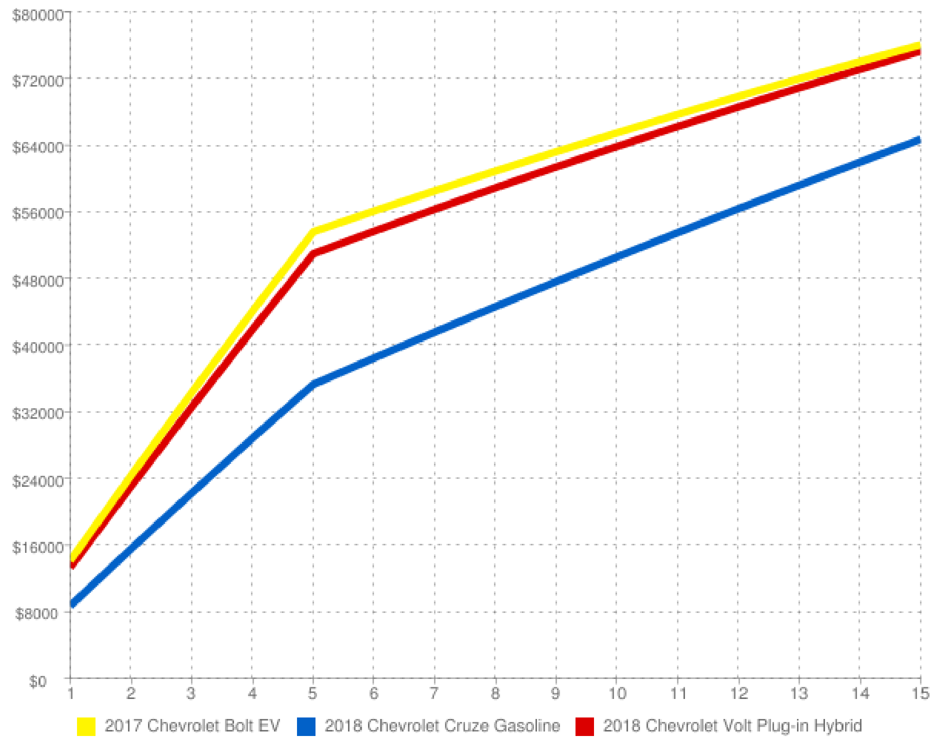


Figure 3: Cumulative purchase and operation costs of various vehicles. Sources: AFDC

In order to balance the future development of EV and its current dilemma, governments of many markets choose to promote EV sales in various ways. On September 8, 2016, California wrote into law a statewide goal of reducing greenhouse emissions 40 percent below 1990 levels by 2030. In order to encourage the use of ZEV to 1.5 million by 2025, the Center for Sustainable Energy (CSE) initiated the Clean Vehicle Rebate Project (CVRP) throughout the state to provide rebates to eligible consumers who purchase or lease ZEVs. From the project inception in 2010 to the end of fiscal year 2014-2015, the program provided nearly 123,000 rebate funds totaling over $260 million. As of September 2017, another 140 million dollars from Cap-in-Trade auction revenue were added on top of the previous annual budget, to replenish the up to $7,000 rebate halted in June[4]. Other state-level incentives include arbitrary use of High Occupancy Vehicle (HOV) lanes regardless of the number of passengers, electricity supply equipment discounts, and charging rate reductions. The federal government also provides tax credits from $2,500 to $7,500 per new EV purchased in the US[5]. Compared with indirect supporting policies such as investment in R&D, directly subsidizing EV sales has the advantage of instantaneously increasing the current EV adoption rate. However, the disadvantage is equally obvious: subsidies may create large deadweight loss, especially in states where clean electricity is not available.

This paper selects the EV market in California to study for at least three reasons. First, studying the EV market has immediate real-world economic significance. Widely considered as a feasible solution to tailpipe air pollution, EV is a relatively new technology that diffused

[4]See more information about CVRP on its website (https:// cleanvehiclerebate .org/eng).

[5]The Alternative Fuel Data Center (AFDC) collects laws and incentives for EV on both state and federal levels (https:// www.afdc. energy.gov/ laws).

rapidly into many developed markets over the past few years, and many believe that the diffusion is just starting. Hence, studying EV is not reexamining obsolete history, but working on contemporary event. Also, the leader state of automotive electrification in the US, California has the highest EV concentration rate: in 2016, there are 6.65 EVs per 1000 people in California, more than twice the number of the third place on the list, Washington. From 2011 to 2016, California accounts for approximately 48% of cumulative EV sales in the entire US. The California market is particularly interesting to look at.

Second, the EV market, like many other new technology markets, is heavily subsidized by governments of different levels, and thus it becomes necessary to evaluate and refine these policies. Because of the "lock-in" nature of technology adoption, severe market failure can happen when new technology tries to penetrate a market "on its own". Mostly, the introduction of a new technology necessarily entails the replacement or elimination of old and inferior technology, a sometimes painful transition related to discounting and even time-inconsistency for individuals. Besides, the positive social welfare created by new technology, such as environmental contribution in the cases of green products, is often in the form of positive externality. Under these circumstances, government might choose to step in to correct the market. Similar government intervention also takes place in the EV market. Currently the market penetration is hampered by EV's comparative disadvantages in prices and in some other functions relative to its traditional counterparts. To promote EV adoption, governments of many markets adopt various promotional policies, such as tax credits and rebate subsidies. These policies are expected to continue in future.

The third reason for studying EV diffusion is that data about EV are carefully collected by many government agencies as well as interested public or private organizations, which is an uncommon case for the study of the consumer side technology adoption. Although not all such data are completely available to the public, those indeed free to use are adequate for conducting preliminary empirical analysis.

4 Empirical Framework

This section describes the sources of data, introduces the empirical structure and presents the results of regressions based on the EV market in California.

4.1 Data Description

Besides the more developed EV market, another motivation for focusing on California is its Clean Vehicle Rebate Program (CVRP). As introduced above, CVRP is a program run by the California Air Resources Board for the purpose of promoting clean vehicle adoption in California. Every time a rebate is granted, the program collects data such as the date, county location, the vehicle's type (BEV or PHEV), the type of applicant (individual, business, government entity or non-profit) and the amount of rebate dollars. Hence, by collapsing the application data to the county level by quarter, we can use the number of EV rebates as a proxy for the demand for EVs. Although the term "clean vehicle" is not strictly limited to EV, the main recipients of the rebates are the battery electric vehicle (BEV) and plug-in hybrid electric vehicle (PHEV) applicants, who account for more than 98% of all applications.

The original dataset spans March 2010 to July 2017 and contains about 205,657 EV rebate applications across all 58 counties in California. After the time frame is limited to 2011-2015 during which the promotional policies such as HOV lane usage were mostly stable, there are 134,536 applications remaining.

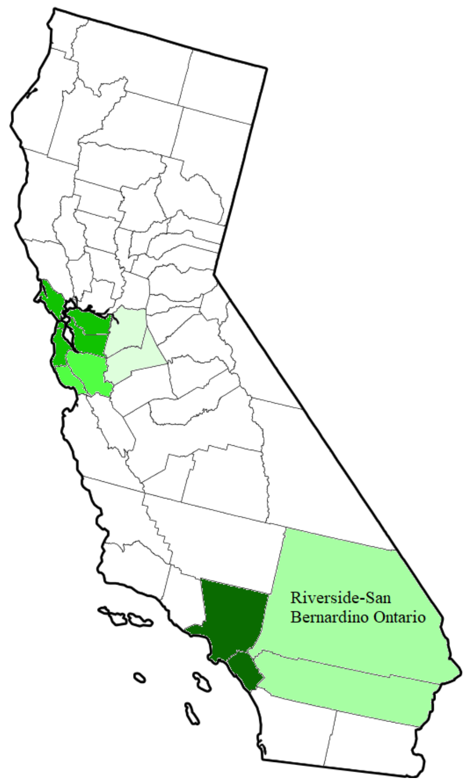


Figure 4: MSA name (number of cumulative applications) color from dark to light: Los Angeles-Long Beach-Santa Ana (51,434), San Francisco-Oakland-Hayward (27,607), San Jose-Sunnyvale-Santa Clara (22,294), Riverside-San Bernardino Ontario (5,736), Sacramento-Arden-Arcade-Roseville (4,673)

To investigate the effect of neighbors across counties, it becomes necessary to create a sensible definition of neighborhood regions. While the principle of contingency can be a simple method of grouping, sometimes this method can generate unrealistic connection among entities which are geographically close to each other but not much economically related; also, the irregular shapes of borders make some level of subjective judgment necessary. As a result, this paper adopts the definition of Metropolitan Statistical Area (MSA), a well defined notion that has already considered the issue of economic ties. Only MSAs with at least two counties are used for this study and there are 7 such MSAs. Because the regression involves log functions and each county must have nonzero applications in all quarters, two more MSAs are dropped. In the end, 15 out of the 58 counties meet the requirements and form 5 neighborhoods. Figure 4 shows the geographical location of them. Because these 15 counties include the two most economically developed and population dense areas of California, the number of observations is only reduced to 111,744, or 83% of the previous sample size. Figure 5 shows the change of cumulative applications of these 15 counties as well as the whole state from 2011 to 2015. Note that potentially because the EV diffusion is just starting, "S-shape" curves have not been generated.

Although other types of data can also measure the level of EV adoption, CVRP application data are used in this research. Unlike vehicle sales or registrations data that are only available for purchase from private consulting companies, CVRP data are completely free for public use on its website. Also, the inclusion of leasing entries, which are sometimes not

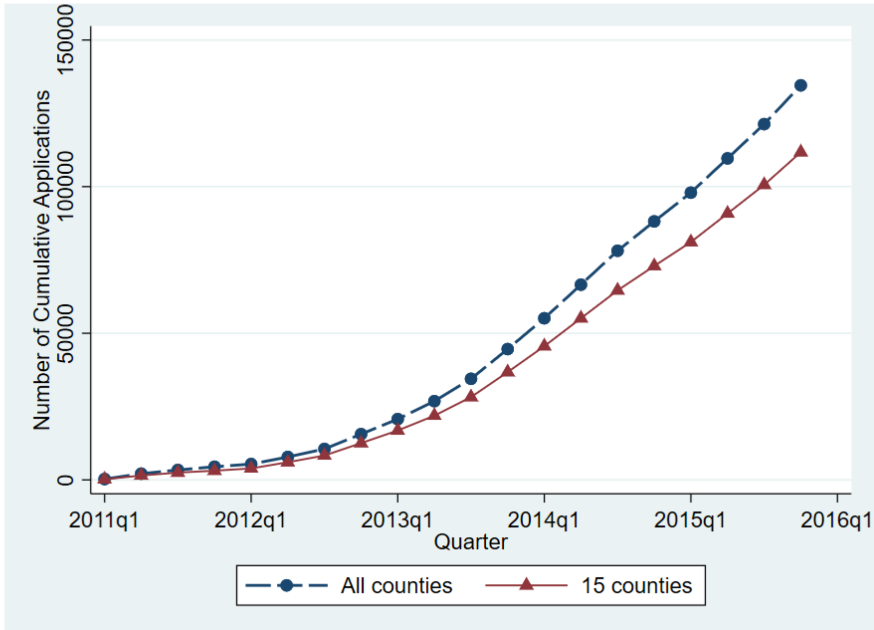


Figure 5: Cumulative EV rebate applications. Source: CVRP data

available in some sales data, are useful for estimating overall adoption behaviors. The only concern with the CVRP data is about representativeness. While applying for a rebate to reduce the purchase cost is apparently a sensible decision for consumers, not every California resident is eligible due to the income cap and some other limitations, such as the maximum total number of permitted rebates per year. Though the situation was not as common in the earlier years as later, funding shortages do happen from time to time. Typically, eligible applicant who submits her rebate application after the fund has been exhausted is added to a waitlist; as soon as more funding is provided, she is considered based on her position on the waitlist. Still, she might feel too impatient to wait for the fund and purchase without the rebate instead. It is also recognized that not every eligible consumer chooses to apply for various reasons. Nonetheless, the data can be trusted for evaluating the trend of diffusion, which is the focus of this study. In one of its reports, CVRP estimates that participation rates from March 2010 through end of March 2015 are at least 74% of the total eligible purchases and leases. Moreover, most counties have participation rates ranging between 65 to 75 percent. The rate is higher than 50% for each year and for each county with sufficient observations, so the data in general reflect well the diffusion pattern across entities and time[6].

The county level demographic data are obtained from American Community Survey 5-year estimates in 2010, which is one year prior to the beginning of my panel data. The Alternative Fuel Data Center provides data about locations and opening dates of EV charging stations, which are like gas stations for gasoline engine cars. As of 2015, there were 691 charging stations in California whose open dates are recorded. Since most historical gasoline price data are not publicly available at the county-level, I use quarterly state-level gasoline price data in California from the U.S. Energy Information Administration. Table 2 provides the summary statistics.

[6]Counties with fewer than 100 rebates for the specific vehicle category are marked as having insufficient observations; for detailed analysis of representativeness, see (https:// cleanvehiclerebate.org/sites/ default/files/ attachments/2015-10%20CVRP %20Participation.pdf).

Table 2: Summary Statistics

Variable	All counties		15 counties	
	Mean	SD	Mean	SD
By county and quarter				
No. of EV rebate applications	117.91	366.72	378.65	633.97
Average rebate dollars ($)	2,216	795	2,296	848
Percentage of BEV application (%)	40.09	36.51	50.18	30.66
Population (thousands)	631.68	139.19	1,679.12	2,310.86
No. of newly deployed charging stations	0.50	1.70	1.24	2.82
By county alone				
No. of households (thousands)	213.67	460.65	568.40	755.58
Median age	38.00	5.76	36.65	3.70
Male (%)	50.76	2.60	49.49	0.55
Household annual median income ($)	55,266	13,310	69,834	11,406
High school attainment (%)	82.46	7.68	85.45	4.98
Bachelor degree (%)	24.61	10.24	36.34	9.78
No. of vehicle ownership (per household)	1.92	0.15	1.85	0.23
Household with 1 vehicle and 2+ members (%)*	14.00	3.08	14.21	2.82
Drive alone to work (%)**	76.91	6.69	74.84	9.95
By quarter alone				
State gasoline price ($)	3.78	0.39	3.78	0.39

Note: The "15 counties" are the counties with at least one other neighbor county in their MSAs and non-zero applications for every quarter from 2011 to 2015.

* Percentage of households with exactly 1 vehicle and at least two household members; further details of this variable will be introduced in the next subsection.

** Percentage of population who drives alone to work.

4.2 Regression Setup

Before introducing the empirical model, I briefly discuss the methodology employed. First, the dependent variable is the quarterly EV demand of a county, which is proxied by the number of rebate applications. For the independent variables, since the theoretical model suggests that the past EV adoption situation of a community (MSA) influences the current EV demand of its entities (counties), it makes sense to focus on the effect of the MSA's average penetration rate. Because vehicle purchase is more often a collective decision of a family than a personal decision and some demographic data are at the household level, the penetration rate is defined as cumulative stock per 1000 households. Alternatively, if we suspect that geographical distance weakens neighborhood effect, then one variable for a county's own penetration rate and another for its other neighbor counties' will be sufficient. However, under the OLS regression model, these two specifications are inevitably biased, because a county's current EV demand and past EV stocks are correlated with too many potentially omitted variables to be all captured. To avoid the problem of endogeneity, I use the penetration rate of all other counties in the MSA except the county itself as the independent variable. The price is that we do not estimate the "correct" parameter γ_i of $P_{i,t}$, but γ_{-i} of $P_{-i,t}$ where $-i$ means all other neighbor counties in the same MSA. Although we have reason to believe that this parameter should be closely related to γ_i, we cannot conclude that it precisely reflects the neighborhood effects defined by the theoretical model. Therefore, I would like to interpret the result of this empirical analysis more as a test of the existence of neighborhood effect than an accurate estimation of its exact magnitude.

Now, consider the case that neighborhood effects are confined within each MSA. The basic structure of the regression model should include the neighborhood penetration rate and some other demographic control variables. Even though the set of control variables can be diverse, there might still be unobservable characteristics among counties and across time that would influence the cumulative past applications as well as current new applications. For instance, although California can be generally classified as a modern liberal state on the political spectrum, some counties might be "greener" than others. Since counties geographically closer to each other are more likely to share similar ideology, the opinion on environmentalism and energy conservation can be an omitted variable. Also, technological progressions frequently happen in the EV industry across time, and it is hard to capture and compare all characteristics of vehicles. Hence, our demand data are likely to be serially correlated in an undesirable way which would bias the estimation. Taking advantages of the panel data structure, I include both county-fixed and year-fixed effects to account of the entity-invariant and time-invariant features. Vehicle model-county-fixed effect is another possible way to control for the unobservable attributes of different EV models. Unfortunately, since the CVRP data only record the manufacturer make but not the specific vehicle model, it is unavailable for this research. Other than the limited number of entities, the reason for choosing yearly instead of quarterly fixed effects is that though technology research and developments happen constantly, most consumers would not feel them until a new generation of product is available in the market; for the automobile industry, producers usually introduce new products yearly. Then, the regression model becomes:

$$Q_{it} = \beta_0 + \mathbf{X_{it}}\boldsymbol{\beta_1} + \gamma_{-i}P_{-i,t-1} + F_i + D_t + \varepsilon_{it}.$$

The subscripts i and t identify counties and quarters. $\mathbf{X}_{it}$ is a vector for the county's time-invariant demographic information, such as household median income and percentage of high school graduates. These characteristics are interacted with a linear time trend in order to include the fixed effects. As discussed above, γ_{-i} is the coefficient on the neighborhood effect received from other counties inside the MSA. F and D represent county and year fixed effects respectively. $P_{-i,t-1}$ is calculated as

$$P_{-i,t-1} \equiv \frac{\text{MSA's cumulative applications}_{t-1} - \text{County i's cumulative applications}_{t-1}}{\text{MSA's number of households} - \text{County i's number of households}}.$$

Concerns about endogeneity could still exist even after control variables and fixed-effects are included, due to reflection between the stock and flow variables. To see this, note that a county's current demand of EVs would affect its neighbors' demands, whose influence would again reflect on the county's demand in future. A similar study by Li et al. (2017) about the indirect network effect of EV demand and deployment of charging station deals with the problem by adopting an instrumental variable; they use the gasoline price as an instrument for EV demand because higher gasoline price should induce more people to buy EVs. I consider another variable for instrumenting the neighbor counties' cumulative penetration rate: the percentage of households with at least two members and exactly one vehicle. While the choice of instrument might seem counter-intuitive at first, it is based the market evidence that few people choose EV as their first car, primarily for concerns about EV's maximal driving range problem as described previously. Households with at least one other vehicle, therefore, are more likely to purchase EV. Also, automobiles are durable goods that exhibit sharp diminishing marginal utility in quantity, so a family is unlikely to purchase too many cars. Thus, this variable captures the proportion of high EV demand type households in a county and is correlated with the total demand. On the other hand, this specific characteristic of a county should not directly affect the EV demand of its neighbor counties. The only concern here is that there might be spatial correlation of the vehicle ownership characteristics within an MSA; this correlation can be easily controlled by adding a county's own high-demand household ratio as control variable into the equations. To introduce time variation to the instrument, I multiply it with the lagged number of cumulative applications in the four MSAs other than the MSA of the county of observation. This strategy is similar to the one by Li et al. (2017); the intuition is that different counties should respond disproportionally to the same state-level trend. One might still reasonably doubt that the choice of this specific type household is arbitrary. If demand data for all types of vehicles were available, it is possible to simply use the average household vehicle ownership as the instrument and compare the relative demand of EVs across counties. Without such data, I would have to manually select a group, so some level of arbitration is inevitable here. In summary, the two equations for estimations are:

$$Q_{it} = \beta_0 + \mathbf{X_{it}}\beta_\mathbf{1} + \beta_2 C_i + \gamma_{-i} P_{-i,t-1} + F_i + D_t + \varepsilon_{it} \tag{8}$$

$$P_{-i,t-1} = \eta_0 + \mathbf{X_{it}}\eta_\mathbf{1} + \eta_2 C_i + \phi Z_{-i,t-1} + F\prime_i + D\prime_t + \varepsilon\prime_{it} \tag{9}$$

In the second stage regression (8), C_i is the control variable of a county's own percentage of high-demand type households. In the first stage (9), $Z_{-i,t-1}$ is the instrumental variable.

4.3 Regression Results

With the tools of regression, I try to answer our main question: are there neighborhood effects in EV diffusion among the selected counties in California? Although an accurate estimate might not be sought in this study, the answer to the existence question is generally affirmative. The second stage regression results are presented in Table 3 and the first stage results are in Table 4. The first three columns of Table 3 contain results of simple OLS regression, and the last three columns use instrumental variables. The first and fourth column begin with only year fixed effects; the second and fifth columns add the county-fixed effects; the last columns of both categories further include the demographic characteristics interacted with time trend.

From all of the six columns, we see that the neighbor counties' EV penetration rate, defined as the cumulative EV rebate application per 1000 households in other neighbor counties, has a statistically significant positive influence on a county's current number of rebate applications. Because a county's own demand for EV should not be directly influenced by its neighborhood's adoption rate after other are characteristics controlled for, we have reason to believe that this positive correlation implies the existence of neighborhood effects: the more neighbors who have adopted the new technology, the more likely is the person to purchase an EV herself. In particular, under the log-log specification, IV(c) shows that on average for a county, a 10% increase in its neighborhood penetration rate would result in a 7.82% increase its own quarterly EV demand. Again, I would not encourage too much interpretation of the specific number here, for this is only an estimation for the parameter $\gamma_{-i,t}$, or the "indirect" neighborhood effect. Had another variable such as own penetration rate been included in regression, one would expect to see the coefficient of neighborhood's penetration rate changes. Also, even after several methods of control have been applied, there are still concerns about omitted variable bias because of the complexity of vehicle demand estimation. I address these considerations in the next section.

It is noticeable that from IV(a) to IV(c), the numerical value of the neighborhood effect sharply decreases as county fixed effects and demographic controls are entered in the regression. In other words, without controlling for the time-invariant factors, there is a large upward bias in estimating the neighborhood effect. This result affirms the hypothesis that EV demands are positively serially correlated. Ideally, these correlations should be assimilated by other observable characteristics; however, since automobile purchase is a highly complicated economic decision and the aggregate demand for new vehicles can be influenced by so many factors, the control variables will hardly be sufficient to capture all other omitted variables. Hence, the fixed effect model helps a lot in this kind of estimation. Because of this trend of decreasing coefficient, it is well possible that when more control variables are added, the coefficient might further drop.

Unexpectedly, the own high-demand household rate term has a negative coefficient estimate in all columns, although it is not significant in IV(c). Combined with the positive term for the instrumental variable in the first stage, the result states that this characteristic of a county is correlated positively with the cumulative stock but negatively with the current demand. After examining the model and data, I consider two explanations. First, because the high-demand vehicle households more readily adopt EV, they may respond rapidly to early demand shocks but less to later shocks. In this case, their influence on the cumulative stock would be persistently positive, yet in future periods their presence would actually decrease the short-run demand. To test this hypothesis, I conduct another regression with the neighborhood current EV demand rather than cumulative penetration rate as the endogenous dependent variable in the first stage. Were this postulation correct, we would expect to see the coefficient for the same instrument in the first stage turn negative as well. The result is partially confirmed here: although the term is still positive, its value is only 0.092, much smaller than the previous 0.217. On top of this reason, the comparison of cumulative stocks between counties with above-average high-demand household rates and those with lower than average rates, as shown in Figure 6, may provide another explanation to the

Table 3: EV Demand

Variable	**OLS(a)**	**OLS(b)**	**OLS(c)**	**IV(a)**	**IV(b)**	**IV(c)**
ln(neighborhood penetration rate)	0.714*	1.159***	1.093***	3.044***	1.204***	0.782**
	(0.381)	(0.102)	(0.109)	(0.999)	(0.182)	(0.360)
ln(own high-demand household rate)	-0.009	-0.137***	-0.139***	-0.620**	-0.148**	-0.079
× ln(lagged state penetration rate)						
	(0.100)	(0.038)	(0.036)	(0.246)	(0.053)	(0.080)
ln(gasoline price)	1.025***	0.803***	1.053***	-0.049	0.783***	1.364***
	(0.257)	(0.197)	(0.175)	(0.526)	(0.199)	(0.373)
ln(household income) × time trend			0.007			0.015
			(0.013)			(0.014)
High school rate × time trend			-0.113			-0.179
			(0.270)			(0.247)
Median age × time trend			0.002			0.002
			(0.004)			(0.004)
Observation	300	300	300	300	300	300
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effect	No	Yes	Yes	No	Yes	Yes

Note: the dependent variable here is the county's log of quarterly EV rebate applications. Neighborhood penetration is defined as cumulative applications per 1000 households in all other counties of the MSA except the county of observation State penetration is defined similarly over the other 14 counties. Due to the lack of county -level historical data, gasoline price is a state-level variable. *, ** and *** are for $p < 0.1$, 0.05 and 0.01.

Table 4: Neighborhood Penetration Rate

Variable	**OLS**
ln(neighborhood high-demand household rate) × ln(lagged state penetration rate)	0.217***
	(0.040)
ln(own high-demand household rate) × ln(lagged state penetration rate)	-0.012
	(0.039)
ln(household income) × time trend	0.039***
	(0.010)
ln(gasoline price)	0.928***
	(0.046)
High school attainment × time trend	-0.343**
	(0.137)
Median age × time trend	-0.001
	(0.001)
Observations	300
R-squared	0.8207

Note: dependent variable is the log of neighborhood penetration rate. County and time fixed effects are both included. *, ** and *** are for $p < 0.1$, 0.05 and 0.01 respectively

reversed effect. The dotted line plots the ratio of the difference between the two types with respect to the below-average-type. Besides the smoothing line which corroborates the previous explanation of diminishing returns, also notice that the high-type had a lower demand prior to the second quarter in 2012, after which a large jump soon reversed the comparison. This jump could come from uncaptured policy changes happening then. When the time of the IV(c) regression is limited from 2012 to 2015, the coefficient for own high-demand household rate does become positive. Result with the trimmed time period are presented later in Table 5.

Among other control variables, the gasoline price has a statistically significant coefficient estimate in all columns except IV(a), so the positive relation between gasoline prices and EV demand is confirmed. Most demographic control variables turn out to be not statistically significant but have the expected signs. For instance, household median income has a slight

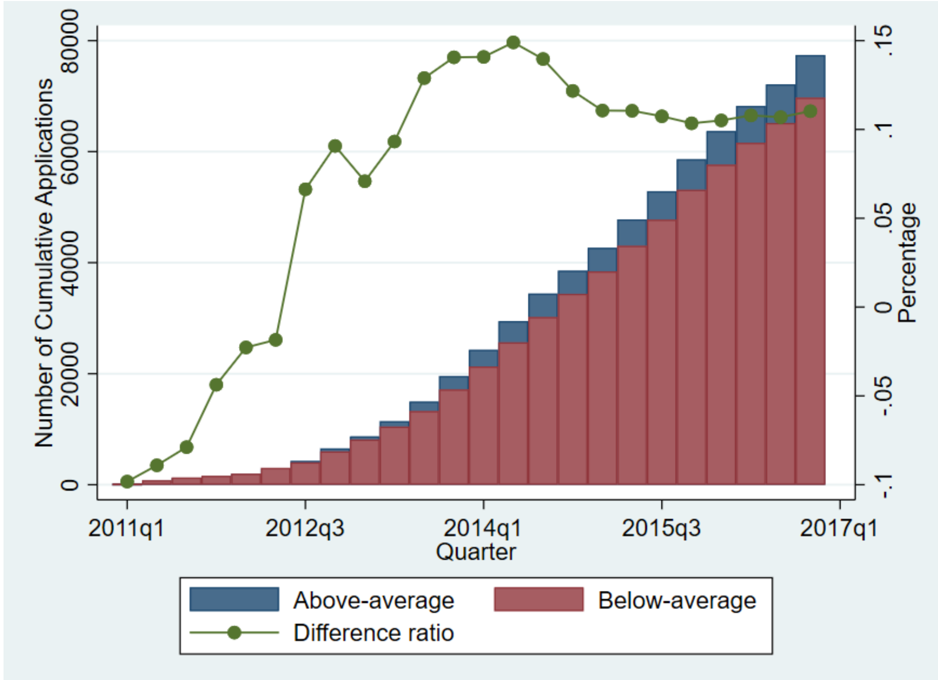


Figure 6: Cumulative applications comparison between counties with above-average and below-average high-demand household rates

positive correlation. However, interestingly, the coefficient estimate for high school attainment rate is negative in both OLS(c) and IV(c), despite the low significance. Because this term is interacted with a linear time trend, it could suggest that the demand growth rate is higher among counties with greater "low-educated" populations. If the county fixed effect is not included and the demographic data alone are used as control variables, the coefficient is still negative, so there is possibly a negative effect of high school attainment on EV demand. Stereotypically, one might think that the more educated would better understand the ecological implication of environmentalism and thus would be more willing to purchase green products such as EV. In fact, when the control variable for annual income is not included, we do see a positive effect of high school attainment rate. When income levels are controlled, the regression shows that more educated population do not have a comparatively higher average demand for EVs than the less educated. It is worthwhile to see whether the result can be replicated for other green products.

Figure 7 shows the observed and predicted cumulative diffusion curves for the 15 sample counties. In general, the model predicts the data well, except that we do observe a slight pattern of nonlinearity. This might result from the progression of the EV technology, or a nonlinear effect of neighborhood itself. As one might be curious about how the model predicts individual counties, I include the comparison graphs for four counties from two MSAs. These counties are pairwise located in the same MSAs, and they are selected to be the counties with highest and lowest number of households in their MSAs respectively. It can be read from Figure 8 that the smaller counties tend to have positive prediction errors while the larger ones tend to have negative errors. Intuitively, because neighborhood effect is mutual between communities, one community might have a positive "net influence" on the

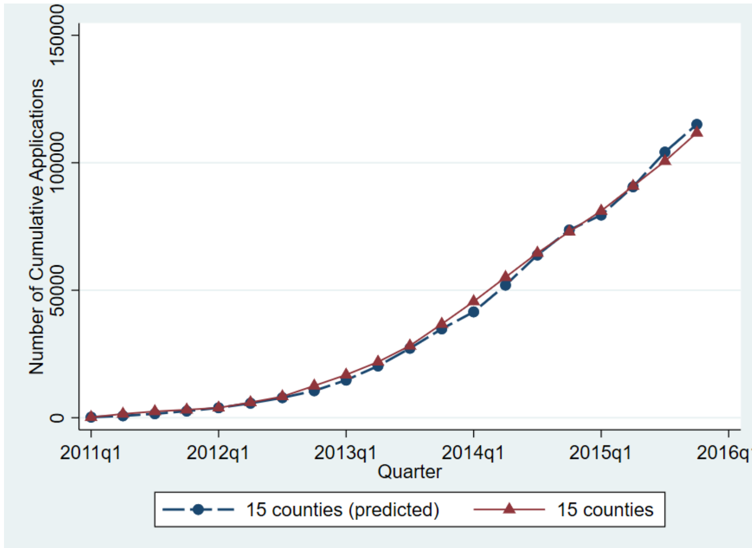
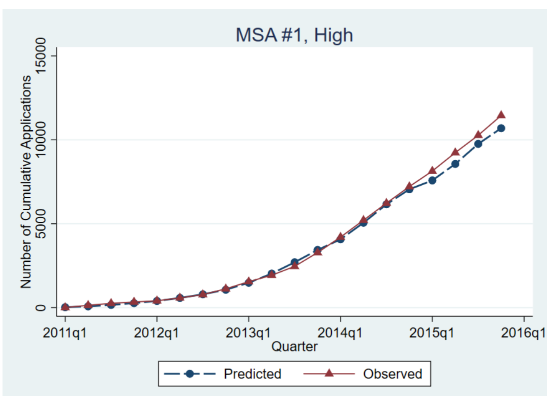
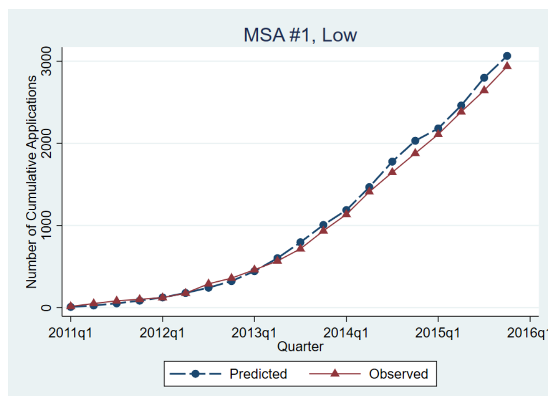


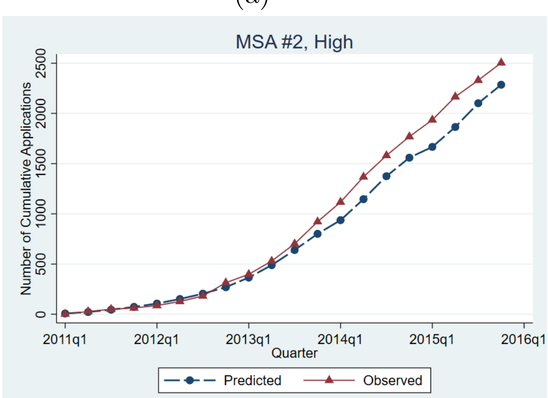
Figure 7: Predicted and observed cumulative diffusion curves: 15 counties



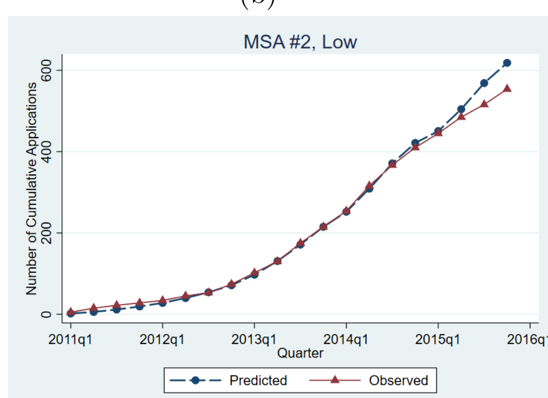
(a)



(b)



(c)



(d)

Figure 8: Predicted and observed cumulative diffusion curves: individual counties

others for economic or geographical reasons, which is analogous to the net exporter position in international trades. Then, we would expect to see upward and downward biases coexist whenever two counties are not completely identical but we only estimate one coefficient of neighborhood effect for all counties. This pattern might be an evidence supporting the heterogeneous effect of neighborhood.

After estimating a universal neighborhood effect in these 15 counties, one might naturally question whether the levels of neighborhood effect are indeed different among individual counties. By the theoretical analysis, heterogeneity in susceptibility to neighborhood effect could influence the diffusion process of communities which are neighborhood to each other, and thus would be crucial for designing the social optimal promotional policies. Although the data do not allow us to separately study each county, we can at least ask what attributes of a county are correlated with the influence on EV demand it receives from its neighbor counties. Reasonably, groups with stronger social networks should be more influenced by the behaviors of the others, but it becomes much less intuitive to decide which observable characteristics can be correlated with the strength of social network. Here, I check one specific speculation: counties with larger relative size in the neighborhood might yield more influence on other counties in the MSA; because the neighborhood effects are mutual between neighbors, they should consequently also receive less of an effect. Again, by "less effect" I do not mean the general neighborhood effect is weaker; instead, it means the "indirect" neighborhood effect from its neighbor counties is less influential to the EV demand of a county.

To study the effect of relative size, I add relative household count of a county to the regression as a control variable, which is computed by dividing the total number of households in other neighbor counties from that number of the county of observation. At the same time, this term is interacted with the neighborhood penetration rate. Since this new variable is also endogenous for the same reason discussed previously, I use the same instrumental variable multiplied by the relative household number ratio in another first stage regression. The coefficient of the interaction term in the second stage with the time range 2011-2015 is not statistically significant. However, if the time frame is restricted to 2012-2015 to avoid the possible policy change in 2012, we have the following second-stage results in Table 5. The dependent variable is still the log of a county's quarterly rebate applications. Both county and year fixed effects are included. First, the coefficient for the interaction term is negative and significant, suggesting that the larger counties do receive less influence from their neighbors. The fact of itself being large, on the other hand, has a positive effect on EV demand as expected. Since the neighborhood effects are mutual in this specification, smaller counties would be more influenced. Hence, the hypothesis is confirmed. Second, compared with IV(c) in Table 3, coefficients for most variables are changed. The neighborhood penetration rate has a larger coefficient, and the gasoline price has a smaller one. The signs for household median income and high school attainment rate are reverted. Thus, we conclude that the model is not stable under different time scope and sets of control variables. Also, notice that the own high-demand household rate term now has a positive coefficient.

Table 5: EV Demand: Effect of Relative Size

Variable	**IV**
ln(neighborhood penetration rate)	1.140***
	(0.347)
ln(neighborhood penetration rate)	-0.231***
× ln (relative household number ratio)	
	(0.068)
ln(relative household number ratio) × time trend	0.064***
	(0.015)
ln(own high-demand household rate)	0.042
× ln(lagged state penetration rate)	
	(0.083)
ln(gasoline price)	0.673***
	(0.126)
ln(household income) × time trend	-0.034***
	(0.010)
High school rate × time trend	0.269*
	(0.161)
Median age × time trend	0.002***
	(0.004)
Observation	240

Note: relative household number ratio defined as the number of house -holds in a county divided by the total number of counties in other neighbor counties. Time range is from 2012 to 2015

5 Conclusion

This research investigates the role of neighborhood effects in the process of new technology diffusion. On the theoretical side, I use a binary choice model to illustrate the influence of a new technology's market share on the adoption decisions of individual consumers in the market. Through comparative statics over the neighborhood effect susceptibility parameter γ, I demonstrate that new technology diffusion is less likely to take place in the high γ type groups; but once enough consumers have adopted, the adoption rates of the high-types will rapidly accelerate and reach higher levels than those of the low-types. Depending on the true nature of the technology, consumers of high-type will either benefit more from an advanced new technology, or become "locked" at the less efficient equilibrium of an undesired technology. Then, in order to reflect the "S-shape" diffusion curve, I extend the model to incorporate linear technology progression. I also discuss the relationship between promotional policies and heterogeneous populations with different γ parameters. Without solving for an explicit form of the expression, I show that the optimal subsidy policy, under some restrictions on the parameters and the assumption that the policy maker aims to maximize the short-run demand for the new technology, is always to subsidize the group more sensitive to the neighborhood effect. When the two groups are less distinct or the adoption rate is closer to 50%, however, the optimal gap between subsidies will shrink to zero.

Next, through an empirical analysis based on the EV market in California, I try to identify the neighborhood effect in technology diffusion in the real world. In summary, the "indirect" neighborhood effect is observed in the 15 relevant counties from 2011 to 2015, as the regression model estimates the elasticity of a county's EV demand with respect to its neighbor counties' cumulative EV penetration rate to be about 0.78. The fixed effects help reduce the upward bias caused by spatial and serial correlations, and the instrumental variable of neighborhood high-demand household ratio, defined by percentage of households with exactly one vehicle and at least two members, is used to solve the endogeneity issue of reflection. For the other control variables, gasoline price and median annual income level have positive correlations with EV demand, but high school attainment rate has a negative correlation, quite contradictory to the popular belief that the more educated population might have a higher demand for green products like EV. In terms of prediction power, this model tends to underestimate the curvature of the real diffusion curve; from comparisons of predicted and observed diffusion rates for neighbor counties with different levels of demand, I postulate that the neighborhood penetration rates might have diminishing marginal effect. Although the data are insufficient to estimate separate coefficients, I consider which attributes of a county can determine its sensitivity to neighborhood effect, and test for a specific speculation: the relative size of a county in its MSA. The interaction term between neighborhood penetration rate and the relative size is statistically significantly negative, confirming my hypothesis that larger counties tend to be less influenced by smaller neighbors, but yield more influence on them.

This research is far from being conclusive. Especially for the empirical part, there are various ways to improve the estimation and various other interesting aspects to look at. Due to the limited resources and time, I could not implement them but briefly discuss them as thoughts on caveats and future studies.

First, despite of all the efforts to eliminate endogeneity problems, the regression model might still suffer from omitted variables bias. One possible source of this bias is a county's preference over green products, which is unlikely fully captured by the fixed effects. Common selections of control variables for this attribute include the League of Conservation Voters scorecard (Heutel and Muehlegger; 2015), support for the Democratic party in elections (Sexton and Sexton; 2013), Green Party registration (Kahn; 2007) and installed hybrid vehicle sales before the introduction of EV (Li et al.; 2017). However, these methods are all more or less not helpful for this study. For example, the LCV scores are on the state level only; California has dominant support for the Democratic party, so the vote difference would not be significant; Green Party registration might be biased by strategic voting; the general vehicle sales data are not publicly available. Another omitted variable is the county-level gasoline price data. Since both variables mentioned here can be positively correlated with a county's neighborhood penetration rate and with the county's EV demand, the neighborhood effect estimation might be biased. Also, as discussed in the beginning of empirical section, there is no reason to not consider a county's own penetration rate in the estimation of neighborhood effect, but I do not yet know an effective method to deal with the endogeneity issue. Any variables that are correlated with the past adoption rate of a county are likely to be also correlated with the county's current demand, so a valid instrumental variable is hard to find.

Second, the aggregate demand format of my data is not completely satisfactory. From the structure of the theoretical model, one would think individual-level decision data are the most appropriate for estimating the neighborhood effect. Vehicles will be categorized by their fuel types, to create an approximation to the binary choice model. Then, I could perform a logistic regression, with individual decisions as the dependent variable and the cumulative penetration rate as the independent variable of interest. The California Vehicle Survey conducted by the California Energy Commission (CES) is close to such a dataset. It asks comprehensive questions on California residents' travel behaviors, vehicle information and demographic characteristics of vehicle owners. In particular, many questions are directly related to EV demand, such as "do you or any other members of your household currently own a Plug-In Electric Vehicle" and "what your top five concerns are about purchasing/leasing an electric only vehicle". The problem is that in order to collect more opinions on EV, it intentionally increases the frequency of EV ownership in the sample to a disproportional level that does not reflect the real EV demand of the market. In other words, there are heavy sample selection biases that would make the estimation biased as well. Hence, it remains a task to seek appropriate individual data.

Third, the empirical model fails to estimate the effect of promotional policies, which is an important part of the initial motivation of this study. To incorporate the effect of subsidies such as the average rebate dollars in the regression equation, one would need to include the average price of EVs and create a combined variable of real price. Then, one must also control for the models, otherwise there might be reverse selection issue that people not only select EV by its price but also "select" price by choosing from different models. Unfortunately, CVRP data do not specify the exact type of model. While for some brands of only limited choices it is possible to infer the model by the information of maker and year, this method of identification is neither accurate nor always applicable. This failure to identify model also makes it impossible to add model-fixed effects into our regression, which is another source of omitted variables bias.

In some sense this paper might propose more questions than it has answered. As we have established a model for the general neighborhood effect, it would be natural to ask what the exact sources of the effect are and how we can identify each source's contribution in the aggregate effect. By isolating different factors of influence, we may consider more targeted policies than simple subsidies. For instance, if it can be shown that "learning-by-doing" is the main source of the neighborhood effects, then it would be beneficial from the perspective of social welfare to help expand the social knowledge capital, such as by instructing consumers and creating channels of communication. Alternatively, if social pressure is the main impeding factor of diffusion in certain communities, then perhaps devising a method to break such norms would be favorable. Young (2009) discusses the theoretical differences in diffusion patterns of three models: contagion, social influence and social learning. The author argues that although the three models all agree on the "S-shape" diffusion curve, their natures leave distinct "footprints" that can be used for ex post identification. However, this quite general method would not work until at least the reflection point has been past, which means that it would not be applicable during the most important launching stage of diffusion. Also, diffusions of different technologies can be so disparate that inference across cases will not provide useful information, so ex post analysis is not always helpful for pragmatic applications. Apparently, other methods of identification are needed. Together these caveats and challenges would be the focus of future research.

Appendix A The Policy Maker's Maximization

This appendix shows how we get (5), (6) and (7) in section 2.2. First, recall that in the budget constraint equation, the "price" of one extra dollar subsidy to either group is the adoption rate of the group, which is a function of the subsidy level. After applying the multiplication rule of derivative, we get the marginal price of s_1 to be $\frac{dP_1}{ds_1}s_1 + P_1$; a similar equation applies for s_2. Rearranging the first order condition would give us equation (5). Then, move the term $\frac{dP_1}{ds_1}\frac{dP_2}{ds_2}s_2$ to the left and $\frac{dP_1}{ds_1}P_2$ to the right; dividing the whole equation by $\frac{dP_1}{ds_1}\frac{dP_2}{ds_2}$ would yield the first part of (6).

Next, we evaluate the marginal utilities. Following the expression of $P_1(t, s_1)$ in equation (4) and ignoring t for one-period optimization only, we can get

$$\frac{dP_1}{ds_1} = \frac{\beta e^{-\beta(\lambda+s_1+\gamma_1(P_1+P_2-1))}}{(1+e^{-\beta(\lambda+s_1+\gamma_1(P_1+P_2-1))})^2}. \tag{A.1}$$

Let $P \equiv \frac{1}{2}(P_1 + P_2)$. The P_1 in the numerator of the right hand side of (6) cancels with the second power of the denominator in (A.1), so (6) actually becomes

$$\begin{aligned} s_2 - s_1 &= \frac{1+e^{-\beta(\lambda+s_1+\gamma_1(2P-1))}}{\beta e^{-\beta(\lambda+s_1+\gamma_1(2P-1))}} - \frac{1+e^{-\beta(\lambda+s_2+\gamma_2(2P-1))}}{\beta e^{-\beta(\lambda+s_2+\gamma_2(2P-1))}} \\ &= \frac{1}{\beta e^{-\beta(\lambda+s_1+\gamma_1(2P-1))}} - \frac{1}{\beta e^{-\beta(\lambda+s_2+\gamma_2(2P-1))}}. \end{aligned} \tag{A.2}$$

The second part of (A.2) dues to the assumption that the two groups have same β, so the terms $\frac{1}{\beta}$ are canceled. A few more simplifications will lead us to the final expression of (6).

To derive the necessary condition of (7), assume that we have found the optimal subsidy levels which we know exist only if $s_2 - s_1 \leqslant 0$. Because $e^{\beta\lambda}$ and the distribution variance term $\frac{1}{\beta}$ must be positive, by the monotonicity of exponential function, it must be that $(\gamma_1(2P-1)+s_1) - (\gamma_2(2P-1)+s_2) \leqslant 0$, which implies (7).

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