Learning, Externalities, and Hybrid Vehicle Adoption

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Abstract

Consumers face considerable uncertainty about the quality of new technologies, and they can learn about them over time as they have more exposure to them. Learning about the quality affects their decision over whether or not to adopt the new technology. Furthermore, new technologies often come in different models that may be heterogeneous in quality. We study the diffusion of hybrid vehicles among consumers. Using data on new hybrid car purchases for 11 different models over seven years, we identify the effect of the penetration rate, or total cumulative hybrid sales per capita, on new hybrid purchases. The penetration rate significantly affects new purchases, and the effect differs by hybrid model. In particular, we find a positive diffusion effect from the Toyota Prius and a negative diffusion effect from the Honda Insight, with elasticities of 0.4 to 0.8 and –0.03 to –0.06, respectively. This finding is consistent with both a model that we develop of model– and firm–specific learning and with anecdotal evidence that the early models (2000-2001) of the Insight were lower quality than those of the Prius. Higher penetration rates of the Insight thus gave a negative signal about hybrid quality and inhibited rather than promoted hybrid adoption. The findings are relevant for policy designed to encourage take-up of new technologies.

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Hybrid electric vehicles are alternatives to conventional, internal combustion engine automobiles that achieve higher fuel economy by combining a conventional engine with a rechargeable battery. The increased fuel economy of hybrids is attractive because of concerns about both climate change and energy security. Transportation accounts for almost one-half of US carbon dioxide emissions, and almost one-half of all petroleum consumed in the US ends up as motor gasoline. Hybrid cars are capturing an increasing share of the domestic automobile market, rising from 0.4% of all retail sales in May 2004 to 3.4% in May 2007. As hybrids are a small but growing component of the vehicle fleet, and may be a significant component of a national strategy to deal with climate or energy security, it is important to know what influences consumers' decisions to buy hybrids rather than conventional vehicles. Because hybrids are a newer technology, issues arise that are similar to those involved with the diffusion of all new technologies, including network effects and learning.

Few studies have examined the determinants of hybrid adoption. This paucity is partly explained by the lack of significant data on this new technology.[1] Gallagher and Muehlegger (2008) examine the role that state and federal incentives, gas prices, and consumer preferences have on hybrid adoption. All three had positive effects, but the magnitude was largest for gas prices and consumer preferences. Kahn (2007) uses data from California and finds that environmentalists, as proxied by a community's share of Green Party voters, are more likely to drive hybrids. On the other hand, many other examples of technological diffusion have been widely studied. For example, Andonova (2006) and Iimi (2005) study the diffusion of cellular phones, and Goolsbee and Klenow (2002) study the diffusion of home computers. As that final paper emphasizes, learning and network externalities play an important role in new technology diffusion.

The purpose of this paper is to study the diffusion of hybrid cars among consumers, and in particular to estimate the effects of learning on consumers' decisions to adopt hybrid cars. We use data on new sales of 11 different hybrid models at the state-quarter level from 2000-2006 and estimate a diffusion model, where the decision to purchase a hybrid is affected by economic incentives, including the price of gasoline and tax incentives for hybrids, as well as the cumulative penetration rate of hybrid vehicles in a particular state. We also present a model of

[1] The Consumer Expenditure Survey, for example, contains data on vehicle ownership, but it only first asked respondents the fuel type of the vehicle (gasoline, diesel, or hybrid) in 2005. The 2006 data set only contains 119 observations of hybrid vehicles, out of more than 56,000 automobile observations.

consumer choice between hybrids and conventional cars, where learning about the quality of hybrids overall or a particular make or model of hybrid enters the agent's decision-making.

The contributions of this work relate to two strands of literature: on the diffusion of hybrid cars in particular and on technological diffusion in general. We add to the small literature on the determinants of hybrid adoption by considering also the important features of uncertainty about quality and learning for this type of durable good. This paper also adds to the large literature on technological diffusion, by considering a case where a new technology is not homogeneous. Different makes and models of hybrids have varying qualities, and this means that consumers get different signals about hybrid quality from their exposure to different types of vehicles. By taking advantage of the variance in quality across models, we can measure how different signals of quality differentially affect consumer take-up.

The first two hybrid models available to American consumers were the Honda Insight and the Toyota Prius, both first introduced in 2000. The Insight initially dominated the market but was soon overtaken by the Prius, and the Insight eventually was discontinued. We document and exploit between-state variation in the initial penetration rates of these two models. In states with relatively more Priuses, consumers were more likely to encounter a Prius, and their beliefs on the quality of hybrid cars were impacted by their exposure to the Prius. We test if the difference between states in the rate of exposure to the Prius and the Insight subsequently affect consumer purchases of hybrids, which we expect if the two models differ in quality and provide signals of hybrid quality.

Empirically, we find significant diffusion effects for hybrid cars, and we find that these effects vary for different makes and models. Overall, a higher hybrid penetration in a state leads to higher hybrid adoption levels in subsequent periods. However, this effect differs for the two models mentioned above. A higher Prius penetration rate leads to more purchases of all models of hybrids, whereas a higher Insight penetration rate leads to fewer purchases. The elasticity of hybrid sales with respect to the market penetration of the Prius in a state is 0.4 to 0.8, whereas the same elasticity with respect to the market penetration of the Insight is –0.06 to –0.03. Thus, the Insight sent a "bad" signal about hybrid quality, while the Prius sent a "good" signal. This is consistent with anecdotal evidence that the Insight was of lower quality than the Prius. Articles in the popular press and reviews from Consumer Reports buttress this claim.

We also find some evidence that the signaling effect differs by both model and manufacturer; Prius penetration has a larger positive effect on other Toyota hybrids than on Honda hybrids, and Insight penetration has a larger negative effect on other Honda hybrids than on Toyota hybrids. The discrete choice model that we develop with learning about differentiated technologies demonstrates how signals from different hybrid models can have these differential effects.

The first section below summarizes the literature on hybrid cars and technological diffusion. The second section presents our models of hybrid diffusion. In the third section we describe our data set, and in the fourth section we present our results. The final section concludes.

I. Hybrid Cars and Technological Diffusion

Conventional automobiles are powered by an internal combustion engine (ICE) running on gasoline or diesel fuel. Battery electric vehicles are powered by rechargeable battery packs, but typically have less acceleration performance and a limited mileage between charge-ups. Though electric vehicles have zero emissions, the electricity generated to recharge the batteries is usually produced by burning fossil fuels. Taking this into account, electric vehicles still produce less carbon dioxide (CO_2) emissions per mile. A hybrid electric vehicle combines the two types of propulsion systems, where the ICE can be used to recharge the battery as well. Furthermore, hybrids can capture some of the energy that is wasted in conventional cars, such as from braking, and use that to recharge, improving their fuel economy even further. Hybrids lack the disadvantage of battery-only electric vehicles of having limited mileage between lengthy recharges. Some hybrids can also be made to "plug in," so that the battery can be recharged either by the ICE or from the electricity from a wall socket. Plug-in hybrids, though, are not commercially available and are not among the models in our data set.

Though hybrids have been produced for more than 100 years, since Ferdinand Porsche designed the "Mixte" in 1901, they have not been widely commercially available until the late 1990s, when the Toyota Prius and the Honda Insight were introduced. The 2008 model year featured 15 new hybrid models. The Prius is the most popular model, surpassing one million worldwide cumulative sales in May 2008, and is the most fuel efficient car sold in the US, according to the EPA.

Because of the small market share and the recent introduction of hybrids, few economics papers study these cars specifically. Gallagher and Muehlegger (2008) examine the effect of federal, state and local incentives on consumer hybrid adoption. Using the same data set that we describe here below, they estimate how much of the growth in hybrid adoption is due to these incentives, how much is due to gasoline prices, and how much to preferences for the environmental and energy security. Each of these factors has a significant effect, with preferences and gasoline prices having the largest. Preferences are proxied for by per-capita Sierra Club membership, quarterly deviation from average temperatures (to measure the salience of climate change) and per capital military participation and war casualties (to measure salience of anti-war sentiment).

Sallee (2008) also focuses on tax incentives for hybrid cars but estimates the incidence of those incentives specifically for sales of the Toyota Prius. He finds that consumers captured a majority of the subsidies, despite the fact that Toyota faced capacity constraints because of excess demand for the Prius during his period of analysis. The offered explanation is that an increase in retail price would have reduced future demand, and so dynamic considerations led to Toyota declining to capture the subsidies. Kahn (2007) estimates the effect of preferences for environmental quality on hybrid purchases. Using data from California and proxying for environmentalism with a community's share of Green Party voters, he finds that environmentalists are more likely to buy hybrids, as well as use public transit and consume less gasoline. De Haan et. al. (2006) use Swiss data on buyers of the Prius to test for evidence of a rebound effect from its purchase. While the most apparent rebound effect is probably the decision to drive more miles in a car that is more fuel efficient, they do not test for this effect (since they lack data on miles driven). Rather, they test for two other rebound effects. First, hybrid buyers could have switched from already fuel-efficient cars to the Prius. Second, average vehicle ownership could increase, if hybrid buyers are using the hybrid in addition to, rather than instead of, another car. They find no evidence of either rebound effect from a survey of 367 Prius buyers. Lamberson (2009) fits data on aggregate US hybrid sales to two diffusion models: the Bass model and the Gompertz model. The Gompertz model forecasts higher future growth rates of the hybrid market and is more consistent with industry expectations.[2]

[2] Papers that study the diffusion of non-hybrid automobiles in a similar fashion include Lescaroux and Rech (2008), Medlock and Soligo (2002), and Greenman (1996).

The diffusion of a new technology through the economy is an important question and one especially relevant to climate policy. Not only hybrid cars, but low carbon technologies like carbon capture and storage (CCS) are potentially essential ingredients to an effective policy regime to combat climate change. Though the economics literature is sparse when it comes to hybrid cars, it is fortunately rich with papers that study the diffusion of other technologies, or diffusion more generally. Geroski (2000) provides a survey of the literature on technological diffusion, and he focuses on explanations of the dominant stylized fact: the usage of new technologies over time typically follows an S-curve. Of particular interest in our paper is the effect of learning and networking effects on the diffusion of technologies. Manski (2000) reviews the literature on social interactions in general, where the actions of some users may affect the actions or outcomes of other users. Heidhues and Melissas (2006) provide a model of technology adoption with cohort and network effects. Peer effects have also recently been studied in the choice of employee retirement plans (Duflo and Saez 2002), health care plans (Sorensen 2006), and medical procedures in developing countries (Kremer and Miguel 2007).

Goolsbee and Klenow (2002) look for learning and networking effects in the diffusion of a consumer technology, home computers. Using cross-sectional data on 110,000 households in 1997, they find spillover effects from computer users: households are more likely to buy home computers in areas where more of their neighbors own computers. This peer effect is larger for heavy computer users and with use of the internet and email, consistent with network effects. An important issue with the estimation of peer effects is ensuring that the estimates found truly are causal peer effects and do not merely reflect correlated unobservable characteristics. Their solution to this potential problem is using instrumental variables.

A focus of our empirical analysis is heterogeneity in the new technology. How do different models of hybrid cars diffuse among consumers, and how do penetration rates of various models affect consumer adoption? Models of the diffusion of heterogeneous technologies extend back at least to Jensen (1983), who models a firm's choice among two competing technologies, about which firms are uncertain. In Jensen's model, adopting one technology gives the firm information about its quality, which the firm uses to update its prior beliefs about that quality. Colombo and Mosconi (1995) and Stoneman and Toivanen (1997) also model the adoption decision among a variety of technologies with uncertain payoffs, although learning in these models comes exogenously from the time since which they were introduced.

Finally, the diffusion of energy efficient and low carbon technologies is a vitally important question relevant to climate policy. McFarland and Herzog (2006) incorporate technological change, specifically CCS, into an integrated assessment model of climate change. They use bottom-up engineering estimates of cost functions for various abatement technologies and simulate how different policies would affect diffusion of these technologies in the energy industry. Rose and Joskow (1990) also study the diffusion of new technologies in the electricity generation industry. They find that larger firms and investor owned utilities are more likely to adopt new technologies than are smaller or publicly owned firms.

II. Model of Diffusion and Learning

Consider first a static discrete choice model of consumer automobile purchases. Assume that the utility consumer i receives from purchasing auto j is given by

$$U_{ij} = \overline{V}_j + \alpha h_j - \beta p_j + \varepsilon_{ij}$$

where $\overline{V}_{ij}$ is the mean utility derived from automobile j (which could in turn be a function of auto characteristics), α denotes the mean utility derived from a hybrid vehicle, h_j is a dummy variable equal to 1 if a vehicle is built on hybrid technology, p_j is the price of auto j and ε_{ij} is an IID error term drawn from a Type I extreme value distribution.

To capture imperfect consumer learning about hybrid vehicle quality, we assume that consumers observe an unbiased signal of hybrid quality $\hat{\alpha} = \alpha + \nu_i$, where ν_{i} is a random variable distributed symmetrically about zero. Note that

$$E[U_{ij}] = E[\overline{V}_j + (\hat{\alpha} - \nu_i)h_j - \beta p_j + \varepsilon_{ij}] = \overline{V}_j + (\hat{\alpha} - \nu_i)h_j - \beta p_j \,.$$

If individual i is risk neutral, she chooses vehicle $j*$ where $E[U_{ij*}] = argmaxE[U_{ij}]$. Since ε_{ij} is distributed IID with a Type I extreme value distribution, this is a multinomial logit model, and we can express the probability of purchasing vehicle j conditional on the draw of ν_i as

$$\Pr_j \mid \nu_i = \frac{\exp(\overline{V}_j + (\alpha + \nu_i)h_j - \beta p_j)}{\sum_k \exp(\overline{V}_k + (\alpha + \nu_i)h_k - \beta p_k)}.$$

The share of model j in an economy with a sufficiently large number of individuals is the expected value of this probability:

$$Share_j = \int (\Pr_j \mid \nu) f(\nu) d\nu \,,$$

where $f(\nu)$ is the probability density function of the quality signal ν, identical for all individuals i.

For simplicity, assume that only one hybrid vehicle exists, indexed as the first vehicle. Consider how the unconditional share of nonhybrid j changes with the variance of the quality signal of the hybrid, ν. Since ν is symmetric with mean zero, we can identify how the unconditional share is affected by the variance of ν by evaluating the second derivative of the conditional probability with respect to ν.

$$\frac{\partial \Pr_j \mid \nu_i}{\partial \nu_i} = -\frac{\exp(\overline{V}_j - \beta p_j)\exp(\overline{V}_1 + (\alpha + \nu_i) - \beta p_1)}{(\sum_k \exp(\overline{V}_k + (\alpha + \nu_i)h_k - \beta p_k)^2} < 0 \,.$$

$$\frac{\partial^2 (\Pr_j \mid \nu_i)}{\partial {\nu_i}^2} = -\frac{\exp(\overline{V}_j - \beta p_j)\exp(\overline{V}_1 + (\alpha + \nu_i) - \beta p_1)}{(\sum_k \exp(\overline{V}_k + (\alpha + \nu_i)h_k - \beta p_k)^2} \left[\frac{2\exp(\overline{V}_1 + (\alpha + \nu_i) - \beta p_1)}{\sum_k \exp(\overline{V}_k + (\alpha + \nu_i)h_k - \beta p_k} - 1 \right]$$

Note that

$$\frac{\partial^2 (\Pr_j \mid \nu_i)}{\partial {\nu_i}^2} > 0 \Leftrightarrow \frac{\exp(\overline{V}_1 + (\alpha + \nu_i) - \beta p_1)}{\sum_k \exp(\overline{V}_k + (\alpha + \nu_i)h_k - \beta p_k} > \frac{1}{2} \,.$$

The expression on the left hand side of the last inequality is the probability of choosing the hybrid car, condition on the signal ν_i. If this probability is less than one-half, a mean-preserving spread of beliefs about the quality of hybrid technology lowers the market share of non-hybrid vehicles and raises the market share of hybrid vehicles. Note that this result is found without risk aversion in consumer preferences; adding in risk aversion works in the opposite direction.

Endogenous Learning

This model has assumed that the signal about the quality of hybrids is exogenous; it comes from an IID draw of the variable ν_i. What we are interested in, though, is how learning comes from peer effects, and thus is endogenous to the penetration of hybrids in the economy. One way to accommodate that endogeneity is to create a dynamic model of car purchases, where the quality signal is a function of past penetration levels of hybrid models. For simplicity, though, let us maintain a static setting but allow learning to be determined by the penetration of hybrids, where this penetration level is determined exogenous to the model.

Relative to the previous model, in which consumers receive an imperfect signal of hybrid vehicle quality, here we assume that consumers do not observe hybrid quality initially. Prospective car buyers interact randomly with current vehicle owners – if a prospective buyer interacts with a hybrid vehicle owner, he learns the quality of that model perfectly. In addition, the prospective buyer infers some information about the quality of hybrid vehicles made by that manufacturer as well as the quality of hybrid vehicles in general.[3]

Consumers choose the vehicle with the highest utility, where the utility to consumer i of purchasing vehicle $j \in J$ is given by

$$U_{ij} = X_j \cdot \theta + \hat{\eta}_j + \varepsilon_{ij},$$

where X_j is a vector of vehicle attributes (potentially interacted with consumer characteristics or gasoline prices), ε_{ij} is a mean-zero IID error term with a Type I extreme value distribution, and $\hat{\eta}_j$ is the consumer's assessment of the quality of hybrid vehicle j, normalizing the quality of non-hybrid vehicles to zero.

Assume that each consumer randomly interacts with a single owner of another vehicle. The set of all possible interactions is the set of all vehicle models, and consumer i's interaction is denoted $\omega_i \in J$. Since each consumer randomly interacts with one vehicle owner, the probability that consumer i interacts with an owner of vehicle j is equal to the initial share of vehicle j. Consumer i's assessment of the quality of hybrid j is a function of his interaction ω_i, $\hat{\eta}_j(\omega_i)$, and can take one of four values. First, if he interacts with an owner of a non-hybrid car, then he gets no additional information on hybrid quality, and the assessment remains at the initial value of $\hat{\eta}_j = \eta_0$. Second, if he interacts with an owner of a model j hybrid car, then he learns the true quality of that model, and $\hat{\eta}_j = \eta_j$. He can get an imperfect signal of the quality of j by interacting with an owner of hybrid vehicle $k \neq j$ in two different ways. If the same manufacturer produces vehicles k and j, he infers something about both hybrid technology and the specific technology adopted by that manufacturer, and $\hat{\eta}_j = \alpha\eta_k + (1 - \alpha)\eta_0$. If a different manufacturer produces k, the consumer only infers something about hybrid technology, and $\hat{\eta}_j$

[3] This model is thus similar to the "epidemic" models of technological diffusion, e.g. Griliches (1957).

$= \beta\eta_k + (1-\beta)\eta_0$, where $\alpha > \beta$. To summarize, if consumer i interacts with an owner of vehicle k (so that $\omega_i = k$), then his assessment of hybrid vehicle j is

$$\hat{\eta}_j(\omega_i = k) = \begin{cases} \eta_0 & \text{if } k \text{ is non-hybrid} \\ \eta_j & \text{if } j = k \\ \alpha\eta_k + (1-\alpha)\eta_0 & \text{if } k \text{ and } j \text{ are hybrids by same manufacturer} \\ \beta\eta_k + (1-\beta)\eta_0 & \text{if } k \text{ and } j \text{ are hybrids by different manufacturers} \end{cases}.$$

The probability that consumer i purchases vehicle j, conditional on consumer i's interaction ω_i, is given by

$$\Pr_j \mid \omega_i = \Pr(U_{ij} > U_{ik} \forall k \mid \omega_i) = \frac{\exp(X_j\theta + \hat{\eta}_j(\omega_i))}{\sum_k \exp(X_k\theta + \hat{\eta}_k(\omega_i))},$$

One can also add to the model an outside option of not purchasing a vehicle, but for present purposes this can be lumped together with purchasing a non-hybrid (since both give no information about hybrid quality). Thus, the market share of vehicle j is

$$Share_j = \sum_k (\Pr_j \mid \omega = k) \cdot \Pr(\omega = k).$$

The probability of interacting with an owner of car model k is $\Pr(\omega{=}k)$ and is equal to the initial share of that model at the onset of the consumer's decision. It is identical for all consumers i, since each consumer randomly interacts with owners among the same set of vehicles.

One could solve for fixed point equilibria in this model. Such an equilibrium is a vector of probabilities, $\{p^*(\omega)\}$, equating the share of sales of all models with the proportion of a stock of vehicles. Mathematically, and equilibrium vector of probabilities solves the system of J equations and J unknowns:

$$Share_j = \sum_k (\Pr_j \mid \omega = k) \cdot p^*(\omega = k) = p^*(\omega = j) \forall j \in J.$$

Uniqueness follows if the J equations are independent. We choose not to consider the fixed point equilibria, because it does not apply to the market we study. Hybrid vehicles are a new technology, and the market share for hybrids is growing and therefore not in equilibrium. A more appropriate analysis is to provide a dynamic analysis of the growth of the market share of hybrids with learning.

We keep the static model described above and use it to perform comparative statics. How does the market share of vehicle j change with a change in the initial penetration levels of vehicle j or other vehicles? To answer this question, we simplify the model some by limiting its generality. Suppose that there exist four car models. Model a is a non-hybrid. Model b is a hybrid manufactured by firm Y. Models c and d are hybrids manufactured by firm Z. Thus, we can consider how signals from the same model hybrid, from a different hybrid model from the same manufacturer, and from a hybrid from a different manufacturer each affect the resulting share of each model.

Let the initial distribution of models be given by p_a, p_b, p_c, and p_d, so that $\Pr(\omega = a) = p_a$, and so on. We focus on the share of hybrid model c, given by

$$Share_c = (\Pr_c|\omega{=}a) \cdot p_a + (\Pr_c|\omega{=}b) \cdot p_b + (\Pr_c|\omega{=}c) \cdot p_c + (\Pr_c|\omega{=}d) \cdot p_d.$$

We are interested in how this share changes with changes in the initial distribution of the models. But since all of the p's must sum to one, we cannot evaluate simply $d\,Share_c/dp_a$. Instead, we evaluate the effects of an increase in the initial weight of one model accompanied by an identical decrease in the weight of another model.

First, consider a marginal increase in p_c accompanied by a marginal decrease in p_a, so that the hybrid of interest is has more representation and the non-hybrid has less. The marginal effect on the share of model c is $(\Pr_c|\omega{=}c) - (\Pr_c|\omega{=}a)$. Using the expression above for these probabilities (from the multinomial logit model) and simplifying the results yields

$$\begin{aligned}\partial Share_c = C\{&\exp(X_a\theta)(\exp(\eta_c) - \exp(\eta_0)) \\ &+ \exp(\eta_0)[\exp(X_b\theta)(\exp(\eta_c) - \exp(\beta\eta_c + (1-\beta)\eta_0)) \\ &+ \exp(X_d\theta)(\exp(\eta_c) - \exp(\alpha\eta_c + (1-\alpha)\eta_0))]\}\end{aligned}.$$

The constant C is positive. Each of the three terms (written on three different lines), and this the entire expression, is positive if only if $\eta_c > \eta_0$. That is, when the true quality of hybrid c is higher than the prior belief about hybrid quality, then the share of c will increase when more c models initially are present compared to non-hybrids. Intuitively, the increase in c models relative to non-hybrids gives a higher probability of getting the signal about c compared to getting no signal (from interacting with a non-hybrid owner). If this signal is higher than the prior, then it will increase the probability of buying c. The increased initial share of c also gives a signal about the quality of b and d, but these effects are not as large since they are a weighted average of the signal and the prior. So although the share of b and d may increase, they will not increase as much as b.

We can investigate how signals of other hybrids affect the share of hybrid c. Consider an increase in the initial share of c accompanied by a decrease in the initial share of b. The resulting marginal effect on the share of c is $(\Pr_c|\omega=c) - (\Pr_c|\omega=b)$, which can be simplified to

$$\begin{aligned}\partial Share_c = D\{&\exp(X_a\theta)(\exp(\eta_c) - \exp(\beta\eta_b + (1-\beta)\eta_0)) \\ &+ \exp(X_b\theta)(\exp(\eta_c + \eta_b) - \exp(\beta\eta_c + \beta\eta_b + 2(1-\beta)\eta_0)) \\ &+ \exp(X_d\theta)\exp(\beta\eta_b + (1-\beta)\eta_0)(\exp(\eta_c) - \exp(\alpha\eta_c + (1-\alpha)\eta_0))\}\end{aligned},$$

where D is a positive constant. The term in the first line is positive whenever $\eta_c > \beta\eta_b + (1 - \beta)\eta_o$. That is, whenever the signal about the quality of c from observing c (η_c) exceeds the signal about the quality of c from observing b ($\beta\eta_b + (1 - \beta)\eta_o$), then the share of c will increase with this change in the initial distribution favoring c over b. This is the intuitive and direct effect, but other effects exist that may counter it. These arise because of the signals that models b and c provide about other models. The expression in the second line is positive if and only if $\eta_c + \eta_b > 2\eta_0$, that is, if the average quality of hybrids b and c exceed the prior. The third effect is positive whenever $\eta_c > \eta_0$. These possibly counterintuitive effects arise because each model provides signals about itself as well as about other hybrids, and these signals affect a consumer's decisions about deciding among all models.

Another set of comparative statics that can be examined concern how the true qualities of each hybrid model affect the share distribution. Again focusing on $Share_c$, note that the effect of a change in η_j on this share is

$$\frac{\partial Share_c}{\partial \eta_j} = \frac{\partial(\Pr_c \mid \omega = j)}{\partial \eta_j} \cdot p_j ,$$

since η_j only affects a consumer's choice if she interacts with an owner of model j. Consider first how a change in model c's quality affects the share of model c. It can be shown that this derivative is positive definite. This is no surprise; a higher quality for model c can only increase the likelihood of a consumer purchasing c. More interesting is the effect that a change in a different model could have on the share of c. For example, after simplifying,

$$\frac{\partial Share_c}{\partial \eta_b} = F[\beta\exp(X_a\theta) - (1-\beta)\exp(X_b\theta + \eta_b)],$$

where F is another positive constant. Here, two conflicting effects are present. As the quality of b increases, b is a more attractive model compared to the others, so its share should rise at the expense of the share of c. This is captured in the second term, which is negative. On the other hand, a higher η_b also serves as a signal of the quality of all hybrid models. Thus, the share of hybrid c may increase relative to the non-hybrid. This positive effect is captured in the first term in brackets. It is weighted by β, the weight that the signal of b conveys to c. As this weight increases, the net effect is more likely to be positive. In fact, in the limit of $\beta = 1$, the net effect must be positive, since the signal given by observing b is the same for all hybrids. Note that the weight in this expression is β, since b and c are made by different manufacturers. The corresponding equation for $dShare_c/d\eta_d$ is weighted by α, since both models are from the same manufacturer.

Dynamic Model

Now we explicitly consider the dynamic decisions that consumers face over the purchase of durable automobiles. Consumers face a decision in each period over whether or not to purchase a new vehicle, and if so, what model vehicle to purchase. For simplicity, we assume that vehicles come in three models: two hybrid models, a and b, and a non-hybrid model c. The utility that consumer i receives from a new vehicle j in period t is given by

$$U_{ijt} = f(X_j\theta + \eta_{jt}) + \varepsilon_{ijt},$$

where f is a utility function, X_j is a vector of observable qualities of vehicle j and η_j is the unobservable quality of vehicle j.

In each period, consumer i receives n unbiased, independent signals of vehicle quality, $\{\omega_{i1},\ldots,\omega_{in}\}$– if the kth signal is about model j then $\omega_{ik} = \eta_j + \nu$, where $\nu \sim \mathrm{N}(0, \sigma_j^2)$. The probability with which the signal provides information about a particular model depends on the market share of the vehicle – if a model a's market share is 5% then the probability with which each of the consumer's signals informs his knowledge about model a is 5%. Information accumulates over time; we denote Ω_{it} to be the set of $n \cdot t$ vehicle-signals that a consumer has received from period 1 to period t.

In a given period, we denote the market share of the two hybrid models s_a and s_b. If signals are independent, then the probability of a particular consumer receiving n_a signals of model a and n_b signals of model b is given by the binomial expression

$$P(n_a, n_b) = \binom{n}{n_a} s_a^{n_a} (1 - s_a)^{n-n_a} \left[\binom{n - n_a}{n_b} \left(\frac{s_b}{1 - s_a} \right)^{n_b} \left(\frac{1 - s_b - s_a}{1 - s_a} \right)^{n-n_a-n_b} \right]$$

For the non-hybrid model, we assume that consumers observe vehicle quality perfectly. Consequently, signals about the quality of the non-hybrid vehicle do not change the consumer's assessment of its quality. We normalize the unobservable quality of the non-hybrid model to zero, $\hat{\eta}_c = 0$ for all individuals in all periods. For the hybrid models *a* and *b* we assume that consumers do not initially observe model quality although consumers have an "uninformed" assessment $\hat{\eta}_0 \sim N(\eta_0, \sigma_0^2)$ of the quality of hybrid vehicles.

Consumers form beliefs about the unknown η_j from their set of observations at time *t*, Ω_{it}. If a consumer has received at least one signal of the quality of model *a*, then her unbiased estimate of η_a is based on only those signals received about *a*. The consumer's belief has a mean value of $\hat{\eta}_a = \sum_{n_a} \frac{\omega_{ij}}{n_a}$, and its variance is $\frac{\sigma_a^2}{n_a}$. If the consumer does not receive any signals about the quality of *a* but receives at least one signal about the quality of *b*, then the consumer will base her beliefs on the quality of *a* in part on her prior assessment of hybrid quality and in part on her signals of the quality of model *b*. The mean value of the consumer's belief is then $\hat{\eta}_a = \alpha \sum_{n_b} \frac{\omega_{ij}}{n_b} + (1 - \alpha)\eta_0$, where α is an exogenous weighting parameter. The variance of this estimate is $\alpha^2 \frac{\sigma_a^2}{n_a} + (1 - \alpha)^2 \sigma_0^2$. Absent a signal from either model, the consumer uses her uninformed assessment $\hat{\eta}_0$. The consumer's belief about the unobservable quality of model *b* is defined symmetrically.

In addition to signals of vehicle quality, a consumer can perfectly observe η_j through ownership. Let m_{it} be the vehicle that consumer *i* owns in period *t*, and let $M_{it} = \{m_{it}, m_{it-1}, \ldots m_{i1}\}$ be the set of all vehicles that she has owned up through period *t*. In period *t*, consumer *i* has perfect information on any vehicle model in M_{it}. Therefore, the consumer's subjective assessment of the unobservable quality of model *a* is given by:

$$\hat{\eta}_a(\Omega_{it}, M_{it}) = \begin{cases} \eta_a & \text{if } a \in M_{it} \\ \sum_{n_a} \omega_{ij} / n_a & \text{if } a \notin M_{it} \text{ and } a \in \Omega_{it} \\ \alpha\eta_b + (1-\alpha)\eta_0 & \text{if } a \notin (\Omega_{it} \cup M_{it}) \text{ and } b \in M_{it} \\ \alpha \sum_{n_b} \omega_{ij} / n_b + (1-\alpha)\eta_0 & \text{if } a \notin (\Omega_{it} \cup M_{it}) \text{ and } b \notin M_{it} \text{ and } b \in \Omega_{it} \\ \eta_0 & \text{if } a \notin (\Omega_{it} \cup M_{it}) \text{ and } b \notin (\Omega_{it} \cup M_{it}) \end{cases}$$

The assessment of model b is defined symmetrically.

Given $\hat{\eta}_a$, $\hat{\eta}_b$, and $\hat{\eta}_c$, the consumer decides whether to purchase a new car at price p (which includes the transaction costs of switching vehicles) or hold the vehicle that she owns at the beginning of the period, in which case the vehicle suffers depreciation at a rate δ. We then write the expected utility for consumer i in period t as

$$U_{ij} = E\,[\,f(X_j\theta + \hat{\eta}_j - p)] + \varepsilon_{ij} \text{ if purchasing a new vehicle}$$

$$U_{ij} = E\,[\,f(\delta^v \cdot (X_j\theta + \hat{\eta}_j))] + \varepsilon_{ij} \text{ if keeping old vehicle,}$$

where v is the age of consumer i's vehicle at the beginning of the period. This can be written as

$$U_{ij} = E[\,f(X_j\theta + \hat{\eta}_j - (1 - z_{it})(1 - \delta^v)(X_j\theta + \hat{\eta}_j) - z_{it}p)] + \varepsilon_{ij},$$

where z_{it} is an indicator variable equal to one if the consumer purchases a new vehicle and equal to zero if she keeps her old vehicle aged v. We assume that the error term ε_{ij} is mean zero, IID, and distributed with a Type-I extreme value distribution. The consumer faces four discrete options: keep the old vehicle of purchase a new model of any of the three vehicle models. Consumers maximize total discounted utility with an infinite-horizon and a discount factor β.

This specification of learning about different technologies is similar to that of Jensen (1983). There, however, potential adopters of the new technologies learn about them only through their own use, not through observing the use of others. The model here thus incorporates "epidemic" effects of Griliches into the real options type approach of adoption choice among competing technologies in Jensen (1983).[4]

Under these assumptions, the probability of a consumer choosing each option is given by the standard expression for the multinomial logit problem, given that her choice in period t is based on maximizing her utility on period t. In a dynamic setting, however, the individual maximizes expected total discounted utility, accounting for how her choices in this period affect her utility in future periods. Because we cannot apply multinomial logit probabilities to this dynamic problem, we use value function iteration to solve the model through simulation.

The model can be simulated in the following way. We first choose parameter values. These include X_j and θ, the observable quality components of each model and their contributions to utility (in fact, we need only a scalar V_j for each model to capture this term).

[4] Jensen (1983) assumes only two different technologies and thus us able to generate analytic optimal decision rules. In our more general framework this is not possible, so we resort to numerical simulation methods.

They also include p, the price of purchasing a new car, δ, the depreciation rate, the true values of the unobservable hybrid quality components η_a and η_b, the prior belief of hybrid quality η_0, the weight on a signal of hybrid quality from the other hybrid model car α, and the form of the utility function f. In addition to parameter values, we also set initial conditions, that is, the initial distribution of models and ages of models in the economy. Thus m_{i1} and v_{i1} are initial conditions that must be determined before the simulation. We choose a number of consumers in the economy N and a number of time periods to simulate T.

For each individual, we randomly draw ω_{it}, that is, a model that she encounters in period t, based on the distribution of models in the economy in time t. This draw, along with the consumer's past draws Ω_{it} and her history of ownership M_{it} determine her assessments of the hybrid models $\hat{\eta}$. These assessments and the state variables of consumer i, the vehicle she owns m_{it} and its age v_{it}, determine the probability of her choosing any of the four options. We randomly draw the value of ε_{ij} to determine which option is in fact taken. This simulated outcome determines her vehicle model and age in the next period, m_{it+1} and v_{it+1}. The distribution of vehicle models in period $t+1$ determines the probability of a consumer encountering any of the three models in that period. We simulate this for all N individuals, and repeat the process for all T periods.

Figure 1 presents results from four simulations, each with the same parameter values but with different initial conditions, that is, different initial distributions of vehicle models and ages. The parameter values that are used throughout the simulations are listed in Table 1. Most of the parameter values are arbitrary. Note that $\eta_a = 0$, so that the unobserved quality of hybrid model a is identical to the unobserved quality of the non-hybrid (which is normalized to zero). Note also that $\eta_b = -0.25$, so that the unobserved quality if hybrid b is less than either the other hybrid or the non-hybrid. Model b thus represents a low-quality hybrid. Finally, note that $\eta_0 = -0.2$, so that the prior belief of an individual, before observing either hybrid model, is that its quality is slightly worse than that of a non-hybrid.

The y-axis of Figure 1 measures the share of the vehicle fleet that are hybrids (models a or b) for each of the 30 periods of simulation (measured on the x-axis). Initially in all four simulations, hybrids account for 21% of the vehicle fleet (this is about equal to the steady-state hybrid market share); however, the relative share of model a and model b differ among the four simulations. In the first, unmarked curve, labeled "binit03", the initial share of b models in the fleet is 3%, leaving 18% for model a. The next curve, marked with circles and labeled "binit06," presents simulation results when the initial share of model b is 6%. The curves labeled "binit09" and "binit11" correspond to initial starting shares for model b of 9% and 11%, respectively.

In simulations with a higher initial share of model b, consumers are more likely to get a signal of hybrid quality from model b than they are to get a signal from model a. Because the true quality of model b is lower than that of model a, the resultant subjective assessment of quality $\hat{\eta}$ is lower in simulations with a higher initial share of model b. Thus, we would expect that a higher initial share of b leads to lower adoption of both types of hybrids. This is just what we see in Figure 1, where the simulation with the lowest initial share of model b, 3%, shortly thereafter has the highest hybrid penetration rate. The simulations with higher initial shares of model b, from 6% to 11%, have lower hybrid penetration rates. Note also that this effect is temporary; the hybrid shares converge around period 20 and subsequently bounce around due to the randomness in the simulations. Eventually, the effect of the initial distribution on consumers' assessments of hybrid quality vanishes, because after enough time has passed most consumers have had the opportunity to accurately assess the quality of both hybrid models. Note also that there is significant variability between the simulations from randomness.

The models formalize some intuition about how heterogeneous quality among a new technology is relevant to its diffusion. An available technology is adopted by consumers not just when they are exposed to it, but when they are convinced that it will increase their utility. Being exposed to different models of hybrids with varying qualities will lead to different outcomes for future adoption; e.g., being exposed to a low-quality hybrid will make you less likely to buy that hybrid and may make you less likely to buy any hybrid. Furthermore, this spillover signaling effect should be stronger for hybrids from the same manufacturer then for hybrids from different manufacturers, if consumers believe that hybrid quality is positively correlated among models of a single manufacturer. We will test for these predictions using our data set of new hybrid sales.

III. Data and Empirical Strategy

We use the same data set used in Gallagher and Muehlegger (2008), and a more detailed description of the data is available in that paper. The data set was purchased from JD Power and Associates and is based on proprietary data they collect on consumer purchases of new vehicles.

Purchases are aggregated at the quarter-state level for each of eleven hybrid models. The time period ranges from 2000 Q1 to 2006 Q4.

The data on hybrid car purchases are combined with a number of control variables. Retail gasoline prices for each state are determined for each quarter using data from the Energy Information Administration. State-quarter level demographic data from the Current Population Survey include per-capita income, mean age, proportion female, and percent of residents with a high school diploma or a bachelor's degree. Measures of state tax incentives for hybrid adoption were collected. These can take the form of an income tax credit for the purchase of a hybrid or a waiver of the sales tax on a hybrid car transaction. These incentives can vary substantially both across states and across time, and a value for tax incentives and the state-quarter level has been calculated and is used as a control.

While Gallagher and Muehlegger (2008) focus on how tax incentives, gasoline prices, and ideological preferences affect consumer adoption of hybrids, we are interested in how learning caused by exposure to hybrids affects their diffusion. Thus, in addition to the control variables described above, we also want to find the causal impact of the penetration of a hybrid model in a particular state at the start of period t on purchases of that model as well as other models during period t. For each model-state-quarter, we calculate the cumulative total sales of that model from all previous periods. We also calculate the cumulative total sales of all types of hybrids from all previous periods.[5] These values of cumulative total sales are divided by the state population in a quarter to create the variable for hybrid model penetration.

Figure 2 shows the diffusion of the two hybrid models, the Honda Insight and Toyota Prius, for the entire country, along with total hybrid penetration. It also presents, measured on the right-hand axis, cumulative Prius sales as a fraction of cumulative Insight and Prius sales. The growth in hybrid penetration is approximately exponential. In early years, the market was dominated primarily by the Insight and the Prius. While the Prius has continued to grow, the penetration of Insight sales flattened (Insight was discontinued in 2006). Also, the Prius's share of the hybrid market share has fallen over time, as more models have been introduced (only the Honda Civic hybrid, released in 2002 Q1, was also available until 2004 Q4). Different models clearly had qualitatively different patterns of diffusion. Similarly, it may be the case that the

[5] Note that we need not worry about hybrid sales from before the start of our data set, since none of the models were introduced to the US market before 2000 Q1. The only exception to this is the Honda Insight, which was introduced in December 1999, so we are only missing that one month's worth of sales.

penetration rates of different models had different effects on consumer adoption of hybrids, which is what we test for.

To estimate the learning effects, we employ a fixed effects panel regression at the state-quarter-model level. The dependent variable is the log of per-capita sales of the hybrid model in that state that quarter. This is regressed on the state-level demographic variables, gasoline prices, and state-model-level tax incentives. The right-hand-side variable of interest is the cumulative penetration rate of the new technology, accounting for either all hybrids, or only hybrids of that particular model. The base specification is thus

$$Log\_SalesPerCapita_{imt} = \alpha_{im} + \beta X_{imt} + \lambda Penetration_{imt} + \eta_{mt} + \varepsilon_{imt},$$

where i indexes state, m indexes model, and t indexes quarter. State-model fixed effects are denoted by α_{im}; model-time fixed effects by η_{mt}; and ε_{imt} represents an error term. The controls are included in X_{imt}, and the coefficient of interest is λ, the effect of cumulate hybrid penetration rates.

Our strategy is primarily to exploit variation in early penetration rates of the Insight and the Prius across states. Figure 3 provides a scatter plot of the rate of cumulative Insight sales versus the rate of cumulative Prius sales for the fourth quarter of 2001 (the last period for which these were the only two models available). The values are in total cumulate sales per 1000 population. The plot shows that, although there is positive correlation between states with high Prius sales and those with high Insight sales, these is also substantial variation between states. California and the District of Columbia, for example, have a relatively higher penetration rate of Priuses, while New Hampshire and Wyoming have a relatively higher penetration rate of Insights. Figure 4 presents further evidence of variation in early penetration rates of the Insight and the Prius. It is a histogram of the number of Insights as a percentage of total cumulative hybrid sales by state. Each state is evaluated in the quarter in which its cumulative sales exceed 250 units. The plot shows that, at this early stage in the hybrid diffusion process, there was substantial variation in the fraction of hybrids that were Insights.

We consider several sources of potential bias. First, state tax incentives and gasoline prices may be endogenous to consumer adoption rates of hybrid cars. As discussed in Gallagher and Muehlegger (2008), if state governments choose incentives based on their efficacy in that particular state, then the estimates of the effect of these incentives may be biased downwards. Gasoline prices are unlikely to be endogenous to hybrid sales, since hybrid penetration is so low during this sample period. Another source of bias is the presence of production limitations constraining the sales of some hybrid models early in the sample period. The Toyota Prius, for example, faced excess demand, and many consumers had to be placed on a waitlist to purchase a car. If these constraints affected all states equally, then they would wash out with out time-model fixed effects. We believe this to be the case based on conversations with Toyota employees. Furthermore, we test the robustness of the results to omitting the quarters during which production constraints were binding.

Finally, an important bias that we must account for comes from the fact that we are essentially regressing on a lagged dependent variable, since the hybrid penetration rates are calculated from cumulative sales. We hope to attenuate this bias by allowing for an AR(1) autocorrelation pattern in the error term ε_{imt}. By doing so, however, we forfeit the ability to include a set of state-model fixed effects α_{im}.

IV. Results

The base case regression results are presented in Table 2. In all specifications, all of the state-quarter level demographic data and gasoline prices are included, as are all state-quarter-model level tax incentive data. We initially use three different measures of the penetration of hybrids. In column 1, the dependent variable of interest is the log of the penetration rate of all hybrids in the state, that is, the total cumulative sales of all models divided by the state's current population. The estimated coefficient is significantly positive; a one percent increase in the penetration rate increases the per capita sales of hybrids by about 0.19%. In column 2, we use a different measure of hybrid penetration, looking only at the penetration rate of hybrids of the same model as the observation. Here, the coefficient is negative but insignificant. In column 3, we regress per-capita sales on the own-model penetration rate as well as on other-model penetration rate, i.e., the per capital total cumulative sales of all hybrid models other than the model in that particular observation. The estimated coefficient on own-model is still negative and insignificant. The coefficient on other-model hybrid is positive and significant. This suggests that the learning effect from the penetration of hybrids may be coming from other hybrid models.

In columns 4 and 5 of Table 2, we perform the same regressions, but we allow the error term to follow a dynamic AR(1) process. This will control for a state-model level unobservable trend that cannot be picked up by the fixed effects alone. However, including this specification of the error term means we drop those state-model fixed effects. The results from columns 4 and 5 show that doing so does not qualitatively change the results, but it increase the magnitude of the marginal effect. The effect of the penetration of all models of hybrids is now about 25% larger. When considering own-model and other-model effects separately, the own-model effects coefficient is now much more negative and statistically significant. For other-model effects, the effect is about twice as large.

The results of Table 2 demonstrate how different models can impart different signals about unknown hybrid quality and thus lead to different diffusion rates. Table 3 examines this effect more closely by running regressions that include all model observations but look at penetration effects separately for the two hybrid models first introduced: the Prius and the Insight. Column 1 regresses the log of per-capita sales on the total cumulative state-level penetration of each of these two models separately. The effect of the Prius is positive and statistically significant; for the Insight the effect is negative but insignificant. In column 2, we also include a term for total hybrid penetration, in addition to these two models. This term is negative but insignificant. The coefficient on Prius is increased accordingly. Finally, column 3 separately includes own- and other-model hybrid penetration effects in addition to the Prius and Insight penetration effects. The Prius and Insight effects are still positive and negative, respectively, and again only the Prius effect is significant. The own-model effect is significantly negative, but smaller in magnitude than the Prius effect. The other-model effect is not significant.

The results from Table 3 are consistent with the theory presented above about heterogeneous quality of a new technology. If the Prius was a high-quality hybrid compared to the other models, then its signaling effect should be more positive than the others. Here, it appears to have provided a positive signal, and some evidence suggests that the Insight provided a negative signal of hybrid quality. This is consistent with anecdotal evidence from model sales and from stories in the media about the quality of these two models. As mentioned earlier, the Prius has become the top-selling hybrid model in the US, surpassing one million new sales, while the Insight has been discontinued. Some have argued that the fact that the Insight's hybrid technology did not perform as well, or that it only had two seats, made it less popular. An early review of the 2001 models of both the Insight and the Prius provides further evidence (Consumer

Reports 2000). The review claims that the Prius is the first hybrid that can "seriously compete with conventional cars." It is called "a worthy contender and a legitimate choice for everyday use." The Insight, on the other hand, was cited for "a lack of accommodations, comfort, and drivability;" the ride is "barely tolerable." Also, the Insight's design, compared to the more conventional Prius, may have doomed it (Patton 2007).

The model also predicts that hybrid of heterogeneous quality will have different signals about the quality of other hybrids depending on whether or not they are from the same manufacturer. A good quality signal from a Prius should be larger for other Toyota models than for models from other manufacturers, and a bad quality signal from an Insight should be more negative for other Honda models. This prediction is tested in Table 4. Column 1 replicates the results from Table 3 for comparison. In column 2, a Prius effect is included along with total hybrid penetration. The Prius effect is interacted with indicator variables for Honda models and Toyota models. Both of these interaction terms are positive, indicating that the Prius gives a positive quality signal about hybrids from both manufacturers. This is consistent with the model above when $\beta > 0$, that is, the signal from one manufacturer's model to another manufacturer's model is positively correlated. Furthermore, the signaling effect is greater for Toyota models than it is for Honda models, and this difference is statistically significant with a p-value of 0.14. This is consistent with the model when $\beta < \alpha$, that is, the signal from one model is stronger for other models of the same manufacturer than it is for other models of a different manufacturer.

In column 3, we include an Insight effect and interact it with dummies for Toyota and Honda models. The effect on Honda models is negative, but not statistically significant. The effect on Toyota models is actually positive, though statistically insignificant. The positive effect of increased penetration of the Insight on Toyota sales is still consistent with the Insight providing a negative signal; the signal will drop the share of Insight sales, and some of that share may be transferred to Toyotas. Although neither of these interaction terms is significantly different than zero, they are statistically different from each other, with a p-value of 0.013. Thus, the negative signal from the Insight appears to hurt Honda sales more so than Toyota sales. Finally, column 4 includes both the Prius and the Insight effects along with the interaction terms. Again, the positive Prius effect is larger for Toyotas than for Hondas, but that difference is not significant. There is no difference in the magnitude of the Insight effect for Hondas and Toyotas.

V. Conclusion

Hybrid electric vehicles are capturing an increasing share of the domestic automobile market, yet they are still a relatively new and uncertain technology compared to conventional internal combustion engine automobiles. Consumers thus make their decisions about purchasing hybrid cars or conventional cars under uncertainty about hybrid quality. To understand the diffusion of this new technology among consumers, one must understand how signals of hybrid quality from hybrids currently in the market affect consumer decisions. Furthermore, with a heterogeneous collection of hybrid models, it is important to differentiate different signaling effects from these different models. We have presented a model showing how learning about the quality of a new technology can affect consumers' decision and how these signals can have different effects depending on the quality and the manufacturer of the observed model. Using data on state-level sales of new hybrid models, we showed that the diffusion patterns of hybrids are consistent with this learning model. Higher penetration rates of the Toyota Prius are associated with higher per-capita sales of all hybrid models, but especially for Toyota models compared to Honda models. Penetration rates of the Honda Insight have a negative effect on sales of new hybrids, and this effect is more negative for other Honda models.

Our identification strategy exploits variation in early penetration rates of the Prius and the Insight across states. This variation exists and is substantial, as evinced in Figures 3 and 4. We thus would like to think of this analysis as a quasi-experiment, where different penetration rates are randomly allocated to different states and we study the effects on subsequent hybrid purchases. This analysis depends on the exogeneity of those initial penetration rates, which is a strong assumption and one that is quite possibly untrue. If a particular state has a systematic preference for one type of car, it would influence both its early distribution of hybrids as well as its subsequent purchases, leading to an upward bias on our estimated diffusion effect. Thus, we hope to extend the analysis in the future to use an instrumental variables approach to account for the potential endogeneity of the initial distribution of hybrid models. Instruments that might be available for this purpose include the relative distribution of non-hybrid Toyota and Honda models. States may have preferences for one manufacturer over another, or a particular manufacturer may have a better distribution system in place in some places, leading to higher penetration rates of hybrid models. We could also look at dealerships, manufacturing facilities, and import locations to use as instrumental variables.

We have identified an effect from lagged penetration rates on adoption of new hybrid cars that differs by model and manufacturer. We have also provided a theoretical model of learning and technological uncertainty that is consistent with this empirical result. However, the empirical result could be explained by other factors besides learning effects. For example, network externalities may be present; higher hybrid penetration in a state may lead to more mechanics able to service hybrids, which would lower their cost in that state and increase adoption. Our empirical strategy cannot disentangle the learning explanation provided by our model from competing explanations of the diffusion patterns that we see.[6] A useful extension to this paper would be to use additional data to attempt to separate these effects.

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[6] Choi (1997) provides a theoretical model that includes both informational spillovers and network externalities.

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Figure 1

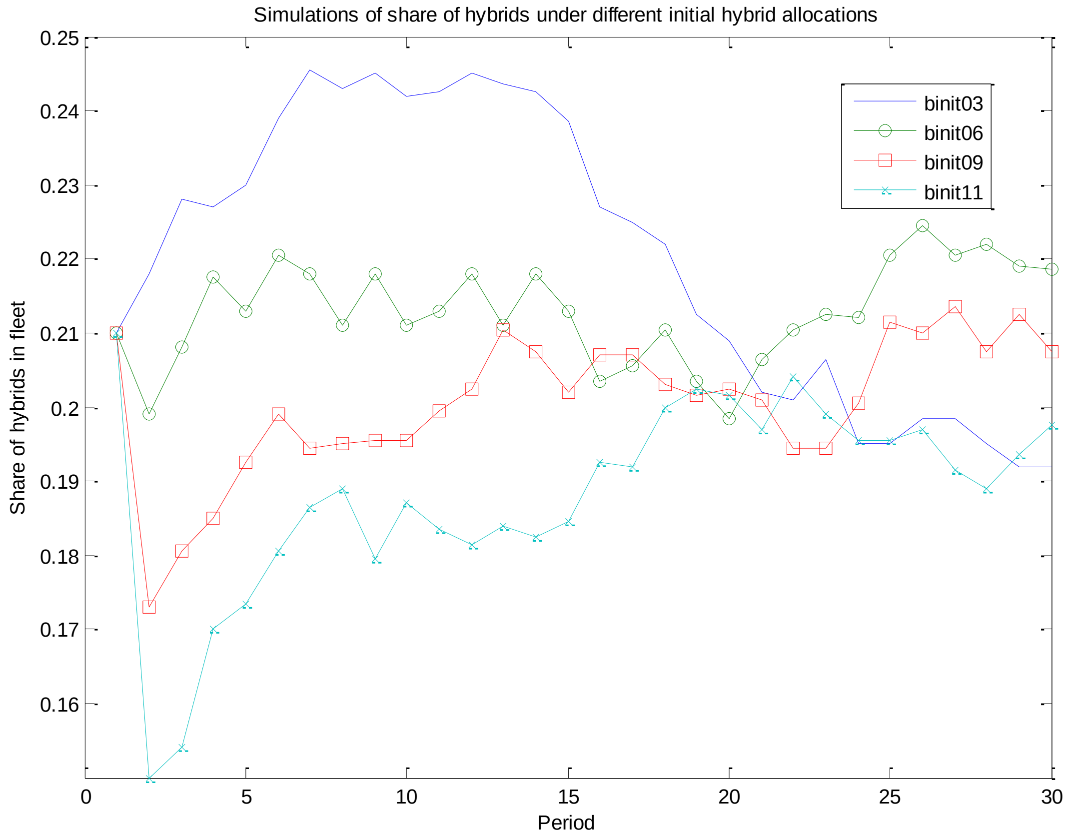
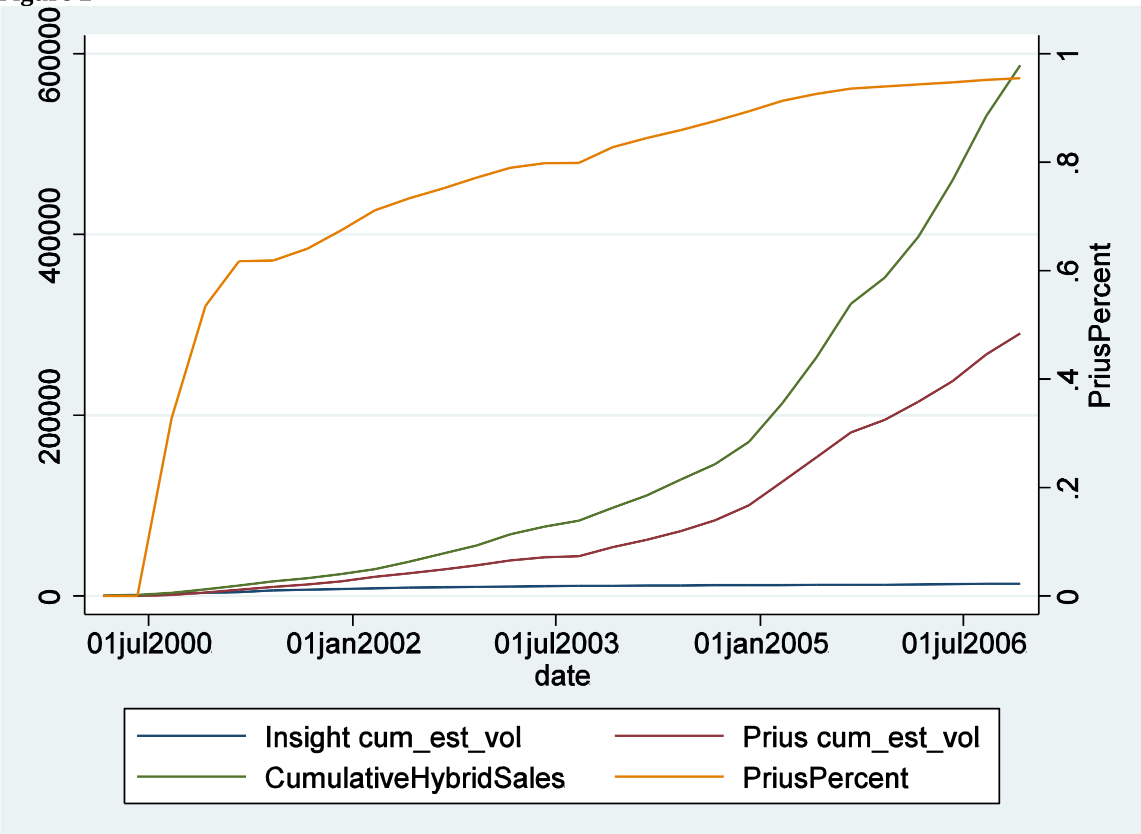

Simulations of share of hybrids under different initial hybrid allocations
Share of hybrids in fleet
Period
binit03
binit06
binit09
binit11
0.25
0.24
0.23
0.22
0.21
0.2
0.19
0.18
0.17
0.16
0
5
10
15
20
25
30

Figure 2



Note: Left-hand axis values are total cumulative sales of Insights, Priuses, and all hybrids in the United States, quarterly, 2000 Q1 – 2006 Q4. The scale on the right-hand axis is the cumulative Prius sales as a fraction of cumulative Prius and Insight sales.

Figure 3

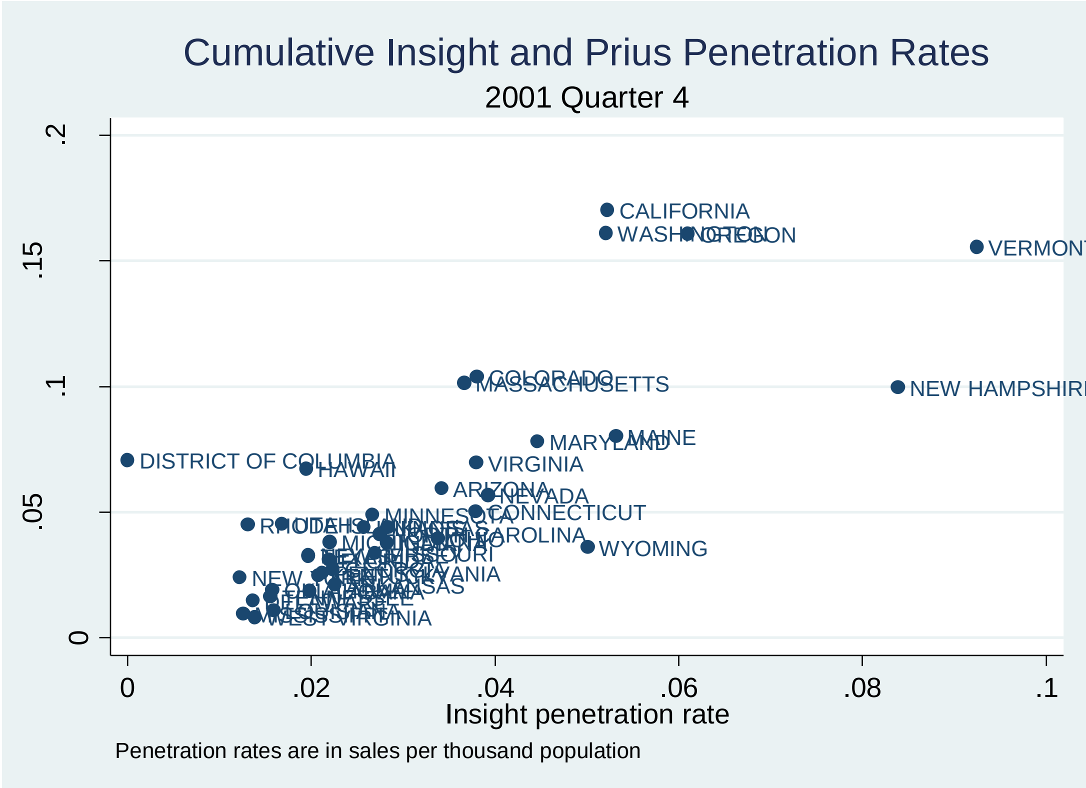

Cumulative Insight and Prius Penetration Rates
2001 Quarter 4
0
.05
.1
.15
.2
0
.02
.04
.06
.08
.1
Insight penetration rate
CALIFORNIA
OREGON
VERMONT
COLORADO
MASSACHUSETTS
NEW HAMPSHIRE
MAINE
MARYLAND
DISTRICT OF COLUMBIA
HAWAII
VIRGINIA
ARIZONA
NEVADA
CONNECTICUT
WYOMING
WEST VIRGINIA
Penetration rates are in sales per thousand population

Figure 4

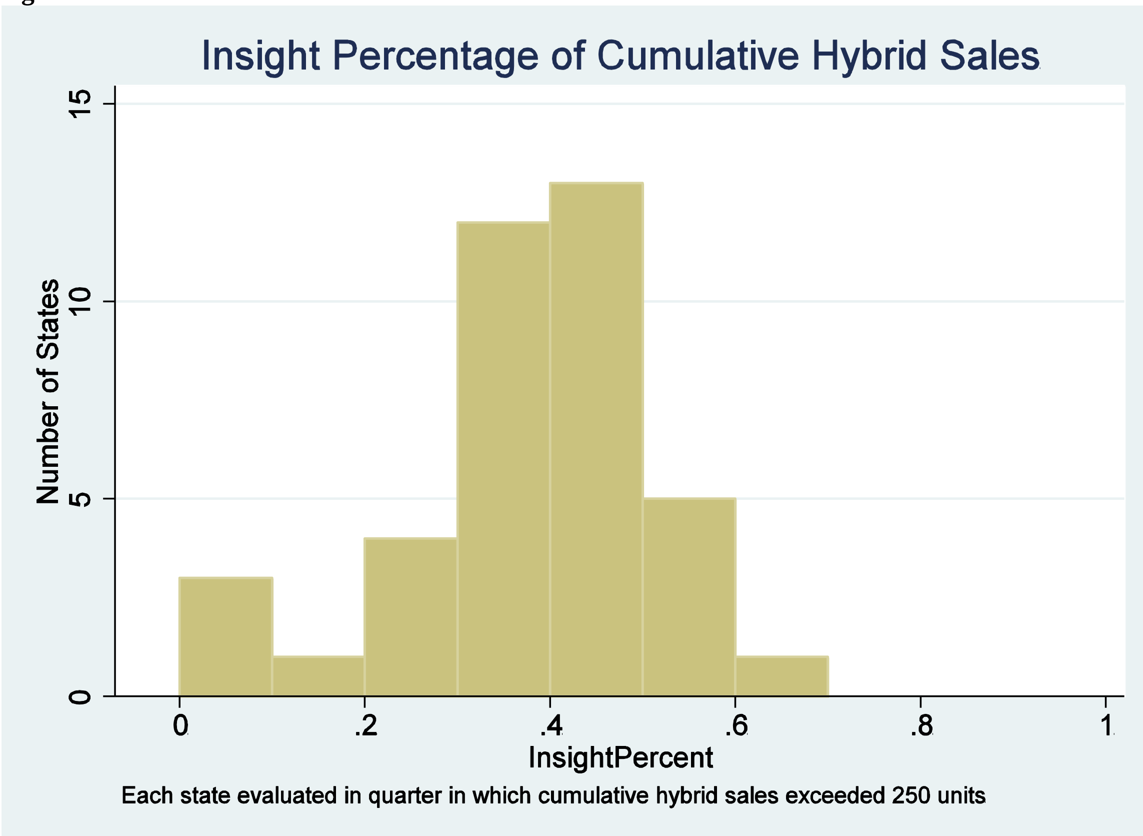

Insight Percentage of Cumulative Hybrid Sales
Number of States
0
5
10
15
0
.2
.4
.6
.8
1
InsightPercent
Each state evaluated in quarter in which cumulative hybrid sales exceeded 250 units

Table 1

Parameter	Value
$\boldsymbol{p}$	5
$\boldsymbol{\delta}$	0.95
$\boldsymbol{V_a\ (= X_a\theta)}$	1
$\boldsymbol{V_b\ (= X_b\theta)}$	1
$\boldsymbol{V_c\ (= X_c\theta)}$	1.1
$\boldsymbol{\eta_a}$	0
$\boldsymbol{\eta_b}$	–0.25
$\boldsymbol{\eta_0}$	–0.2
$\boldsymbol{\alpha}$	0.8
$\boldsymbol{\beta}$	0.95
$\boldsymbol{\sigma_a^2}$	0.5
$\boldsymbol{\sigma_b^2}$	0.5
$\boldsymbol{\sigma_0^2}$	0.5

Table 2

Effects of Hybrid Penetration on Hybrid Adoption					
	(1) logNewSales	(2) logNewSales	(3) logNewSales	(4) logNewSales	(5) logNewSales
Log(hybrid_pen)	0.191			0.252	
	(0.043)**			(0.065)**	
Log(model_pen)		-0.019	-0.043		-0.335
		(0.029)	(0.031)		(0.062)**
Log(other_pen)			0.177		0.351
			(0.045)**		(0.066)**
logPCI	1.991	2.226	1.813	1.581	1.615
	(0.471)**	(0.456)**	(0.446)**	(0.457)**	(0.503)**
logmeanage	-11.181	-9.551	-7.899	-3.781	-5.575
	(3.418)**	(3.187)**	(3.245)*	(3.430)	(1.971)**
logfemale	-3.676	-11.644	-22.833	2.884	-4.614
	(12.483)	(13.625)	(13.477)+	(12.461)	(10.495)
logHSGrad	1.016	1.662	1.659	1.693	1.364
	(0.786)	(0.797)*	(0.811)*	(0.801)*	(0.863)
logBAGrad	-0.094	-0.064	0.008	0.104	0.181
	(0.195)	(0.193)	(0.197)	(0.199)	(0.215)
logStateGasTax	0.631	0.535	0.479	0.531	0.422
	(0.308)*	(0.303)+	(0.308)	(0.280)+	(0.294)
new_hov_lanes	-0.101	-0.118	-0.122	-0.131	-0.104
	(0.059)+	(0.058)*	(0.058)*	(0.069)+	(0.072)
StateTax	0.041	0.045	0.039	0.018	0.007
	(0.026)	(0.029)	(0.029)	(0.026)	(0.029)
Constant	22.594	10.892	-1.109	0.785	2.368
	(15.637)	(14.943)	(15.240)	(5.266)	(0.385)**
Observations	4689	4284	4205	4192	3720
Number of group(model t)	121	111	109		
R-squared	0.68	0.71	0.71		
Number of group(state model)				484	459
Error Structure	Clustered State*time	Clustered State*time	Clustered State*time	AR(1)	AR(1)

Note: **significant at 1% level; *significant at 5% level; +significant at 10% level. All regressions include a quarter-model fixed effect

Table 3

Model-Specific Effects – Prius and Insight			
COEFFICIENT	(1)	(2)	(3)
log_prius_pen	0.398***	0.571***	0.781***
	(0.066)	(0.15)	(0.11)
log_insight_pen	-0.0640	-0.0549	-0.0334
	(0.043)	(0.044)	(0.044)
logPCI	1.267***	1.360***	1.720***
	(0.48)	(0.49)	(0.51)
log_hybrid_pen		-0.221	
		(0.18)	
log_model_pen			-0.512***
			(0.071)
log_other_pen			-0.0887
			(0.10)
Constant	1.738***	1.704***	-0.0119
	(0.31)	(0.31)	(0.44)
Observations	3895	3895	3574
Number of sm	456	456	433

Note: ***significant at 1% level; **significant at 5% level; *significant at 10% level. Standard errors in parentheses, with AR(1) autocorrelation. All regressions also include the same set of controls as the regressions in Table 1.

Table 4

Model-Specific Effects by Manufacturer				
COEFFICIENT	(1)	(2)	(3)	(4)
log_hybrid_pen	-0.221	-0.307*	0.327***	-0.223
	(0.18)	(0.16)	(0.070)	(0.18)
log_prius_pen	0.571***	-0.00595		-0.385
	(0.15)	(0.29)		(0.35)
log_insight_pen	-0.0549		-0.0554	0.0574
	(0.044)		(0.077)	(0.089)
Honda_log_prius_pen		0.549**		0.920***
		(0.26)		(0.33)
Toyota_log_prius_pen		0.729***		1.064***
		(0.27)		(0.33)
Honda_log_insight_pen			-0.150	-0.0995
			(0.099)	(0.11)
Toyota_log_insight_pen			0.0968	-0.124
			(0.11)	(0.12)
logPCI	1.360***	1.505***	1.529***	1.425***
	(0.49)	(0.47)	(0.47)	(0.49)
Constant	1.704***	2.939***	-1.821***	2.277***
	(0.31)	(0.30)	(0.48)	(0.28)
Observations	3895	4079	4008	3895
Number of sm	456	484	456	456
F statistic of test that Honda-Prius interaction term = Toyota-Prius interaction term	-	2.15		1.21
p-value of test	-	.1427		.2716
F statistic of test that Honda-Insight interaction term = Toyota-Insight interaction term			6.16	.06
p-value of test			.0131	.8094

Note: ***significant at 1% level; **significant at 5% level; *significant at 10% level. Standard errors in parentheses, with AR(1) autocorrelation. All regressions also include the same set of controls as the regressions in Table 1.