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Abstract

We study the effect of differences in product quality on new technology diffusion. We propose a model in which heterogeneity in perceived product quality affects consumer adoption. If consumers experientially infer the quality of a technology, an increase in initial exposure to a low-quality product may inhibit subsequent diffusion. Incentives intended to speed up adoption may in fact have the opposite effect, if they propagate low-quality signals. We examine the predictions of the model using sales data for 11 hybrid-vehicle models between 2000 and 2006. Consistent with press reports that the first-generation Insight was perceived to be of lower quality than the first-generation Prius, we find that, conditional on overall hybrid vehicle adoption in the first two years, locations with a relatively high Prius market share experienced faster subsequent adoption than states with a relatively high Insight market share. We estimate the elasticity of new hybrid sales with respect to the Prius penetration rate is 0.30 to 0.55, while the elasticity with respect to the Insight penetration rate is –0.14 to –0.44.

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Encouraging consumer adoption of new technology is viewed as an important part of the solution to many energy and environmental policy challenges. While a long literature models consumer adoption of technology, the literature abstracts away from one important dimension common to many technological introductions. Often, products using the new technology vary in perceived quality. In some contexts, variation arises because the first-generation of a product is of lower quality than more refined, subsequent versions. In other contexts, variation might arise because different firms offer competing products that use the same technology but vary in quality. In either case, low-quality versions of a product may send a negative signal of the technology's quality to prospective buyers and have a deleterious impact on future adoption.

These effects commonly arise for new technologies that improve energy efficiency. As an example, a 2006 report to the Department of Energy on barriers to adoption of compact fluorescent lightbulbs notes "consumers had a number of complaints about the performance of early CFLs, often resulting in long-term distrust of CFLs as a lighting category in general." When the asked by the study authors, one manufacturing representative noted: "Of course the solution to this is for manufacturers and retailers to present good-quality products to consumers. Otherwise poor quality goods will prejudice the buyer, and he may not buy again…not surprisingly, manufacturers often want to jump into the market with a new technology to be one of the first entrants, which means they might introduce a technology prematurely, causing the consumer to develop negative perceptions of the entire lighting category if it does not perform as expected." The authors go on to suggest "Premature release of a product that isn't going to satisfy consumers can hurt both the manufacturer and the industry… This early dissatisfaction could result in a consumer that is unwilling to try a CFL again – even once performance has been improved." [1] In this paper, we formalize this dynamic in a simple model of inferential learning in which two competing models of different quality are offered, and late-adopters infer the quality of the technology from the products purchased by early adopters. We illustrate how variation in the quality of products using new technology can impact the speed at which the technology diffuses. As in the example above, we demonstrate that early adoption of a low-quality product can affect beliefs of prospective buyers and slow subsequent adoption.

Our theoretical model suggests important considerations for government policy related to technological adoption. Incentives have been widely used in the past to promote the adoption of

[1] Quotations from Sandahl et al. (2006), p. 6.5, 6.7, and 7.1.

new technology, partially motivated by the idea that early adopters may help to spread information about the promoted product as well as the quality of the technology more generally. In many cases, though, government incentives favor one version or product relative to another.[2] Our model suggests that incentives that mistakenly target a low-quality version of a new technology may not only be ineffective, but may even slow, rather than speed, overall adoption of the technology. Furthermore, even an incentive that does not differentiate by the versions of the new technology may inhibit diffusion, if low-quality versions are over-represented in the early stages of the product.

We then consider a particular empirical application: hybrid vehicle adoption in the U.S. from 2000 to 2006. 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. Hybrid cars are capturing an increasing share of the domestic automobile market, rising from 0.4% of all retail sales in May 2004 to 3.6% in July 2009. Although still a small but growing part of the vehicle fleet, hybrid vehicles are seen as a significant component of a national strategy to deal with climate or 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. The increased fuel economy of hybrids helps to address both of these policy issues.

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 in 2006.[3]

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 perceived quality and provide different signals of hybrid quality.

[2] For instance, state-level hybrid car incentives often have applied only to some hybrid models (see Gallagher and Muehlegger, 2011, Table 2).
[3] A substantially redesigned Insight was reintroduced to the American market beginning in the 2010 model year, after our data set concludes.

Every diffusion model faces the problem that the installed base may be a proxy for unobserved heterogeneity. We address this problem with two sets of instrumental variables. The first is based on the number of Honda and Toyota vehicles registered in a state in the years before hybrids were introduced. While consumers obviously vary across states in preferences for hybrid vehicles, our identifying assumption is that this preference heterogeneity is uncorrelated with the relative Honda-Toyota market pre-hybrid market shares. Dealer networks, import locations, and consumer brand loyalty may affect the relative initial penetration rates of Priuses vs. Insights, but we expect that these features, which are relevant for our instrument, do not directly affect consumers' decisions on whether or not to buy a hybrid. Our second set of instruments is based on the presence of Honda or Toyota manufacturing facilities in a state. The presence of these plants is a measure of initial market shares of Hondas and Toyotas, but not correlated with consumer preferences over hybrids. We combine this instrumental variables approach with state- and year-fixed effects and a number of demographic control variables.

We find three pieces of evidence consistent with the model of technological adoption with products of heterogeneous quality. Diffusion effects significantly differ by model. A higher Prius penetration rate leads to more purchases of all models of hybrids, whereas a higher Insight penetration rate leads to fewer purchases. We estimate that the elasticity of hybrid sales with respect to the market penetration of the Prius in a state is between 0.30 and 0.55, whereas the elasticity with respect to the market penetration of the Insight is between –0.14 and –0.44. This is consistent with our model if the Insight sends a "bad" signal about hybrid quality and the Prius sends a "good" signal. Articles in the popular press and reviews from Consumer Reports provide anecdotal evidence that the Insight was perceived to be of lower quality than the Prius.

We also find evidence that the information value of the signals sent by the Prius and Insight declines over time. Initially, states with high relative Insight penetration experience lower rates of hybrid adoption compared to states with high relative Prius penetration. After the end of 2002, hybrid vehicle sales grow more quickly in the high Insight penetration states.

Lastly, we find patterns suggesting that the signal value varies with model and manufacturer. Prius exposure has a positive effect on all hybrid sales, but has a larger effect on sales of other Toyota hybrids and a still larger effect on Priuses. Similarly, Insight exposure's negative effect is more negative on Insights than on other models (and in fact is not statistically different from zero on other models).[4]

Previous Literature

This paper contributes to two literatures: the literature on technological diffusion and the literature examining the diffusion of hybrid cars in particular. Several papers in the broader literature on technology diffusion have considered heterogeneous technologies. However, none of those other papers explicitly model the mechanism by which learning about the technology occurs, and none identify either theoretically or empirically how low-quality products can slow diffusion. Jensen (1983) 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.[5] Our theoretical model explicitly models the learning that occurs among consumers, and demonstrates how the resulting installed-base effects can vary by technology and can be negative.

Another relevant sector of the diffusion literature is the "word of mouth" literature, which also considers product quality. Dover et al. (2012) study how the structure of the social network affects the diffusion process, where the network structure can facilitate the spread of information, and Chevalier and Mayzlin (2006) study the effect of online consumer book reviews on consumer adoption. This literature is focused on consumers directly telling others whether or not they like a product. Ours is a contagion model, where consumers are learning about the technology via exposure.

Because of their small market share and recent introduction, a small, but growing literature examines hybrids specifically.[6] In this literature, this paper is the only to model and

[4] A causal installed-base effect may occur for reasons other than consumer/social learning. For instance, “green envy” may create a similar diffusion pattern (Sexton and Sexton 2012), as may network effects or economies of scale in maintenance or repairs. While we are not able to identify or rule out any particular mechanism for generating the causal installed-base effect, we argue that the heterogeneity in diffusion that we see by models is most consistent with our model of consumer learning.

[5] Young (2009) models diffusion and learning with heterogeneity among consumers, not technologies.

[6] This paucity is also partly explained by the lack of significant data on this new technology. The Consumer Expenditure Survey, for example, contains data on vehicle ownership, but it only first asked respondents the fuel

estimate diffusion with products of heterogeneous quality. By taking advantage of the variance in perceived quality across models, we measure how relative penetration of the Honda Insight and the Toyota Prius affect subsequent consumer take-up. The paper most similar to ours is Narayanan and Nair (2013). They estimate a causal installed-base effect of hybrid ownership on hybrid purchases. They demonstrate that fixed-effects estimators are inconsistent, and suggest two solutions: instrumental variables or a new bias-correction approach. We also use an instrumental variables approach, described below, but their bias-correction approach relies on asymptotic properties and requires a large dataset, unavailable to us in our state-level analysis. While they have access to more data points because they use vehicle-level data, they only look at the Toyota Prius and only in California, and thus they are unable to address the heterogeneous effect by automobile model. Other studies of the diffusion of hybrid cars rely primarily on survey data. Axsen et al. (2009) compare stated preference and revealed preference methods of estimating neighbor effects in the hybrid market, using survey data from several hundred Canadian and Californian automobile owners, and Mau et al. (2008) use survey data to estimate neighbor effects in this market.

A number of other papers examine static drivers of hybrid vehicle adoption including government incentives, fuel prices and preferences for environmentalism. Gallagher and Muehlegger (2011) examine the effects of federal, state and local incentives and fuel prices on consumer hybrid adoption and find that the state sales tax waivers are most strongly associated with hybrid vehicle adoption and that fuel prices are positively correlated with adoption of high fuel economy hybrids, but not low fuel-economy hybrids. Beresteanu and Li (2011) and Chandra et al. (2010) also find significant effects from gasoline prices and tax incentives on consumer hybrid purchase decisions. Sallee (2011) estimates the incidence of tax incentives 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. Kahn (2007) estimates the effect of preferences for environmental quality on hybrids. 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 two "rebound effects" from its purchase: hybrid buyers could have switched

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.

from already fuel-efficient cars to the Prius, or average vehicle ownership could increase. They find no evidence of either rebound effect from a survey of 367 Prius buyers. Lamberson (2008) 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.[7]

Finally, the diffusion of energy efficient and low carbon technologies is relevant to climate policy. McFarland and Herzog (2006) incorporate technological change, specifically carbon capture and storage, 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) 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. Bollinger and Gillingham (2012) study the diffusion of solar photovoltaic panels.

The first section below presents our models of hybrid diffusion. In the second section we describe our data set and empirical strategy, and in the third section we present our results. The final section concludes.

I. A Diffusion Model with Heterogeneous Quality

We begin by presenting a model of technological adoption in which different versions of the technology vary in perceived quality. In our model, prospective buyers receive signals of technological quality from early adopters and use the signals to update their priors on technological quality. It incorporates both "epidemic" learning effects from Griliches (1957) and choice among competing technologies as in Jensen (1983). We focus on consumer decisions and disregard other issues, including producer pricing decisions, risk aversion, economies of scale, learning-by-doing or network externalities. Although these are all relevant for technological adoption, they are not the focus of this analysis.[8]

[7] 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).

[8] Other papers that study diffusion in the automobile market without explicitly modeling firm behavior include Kloess and Muller (2011), Kopecy and Suen (2010), Lescaroux and Rech (2008), and Greenman (1996). Exclusion of firm behavior may bias coefficients up. However, our main results lie in the difference between the coefficient on the Prius and those on the Insight. It is unlikely that the bias from omitting firm behavior will affect this difference.

Our objectives are two-fold. First, we demonstrate how early adoption of an inferior product may slow overall adoption. This insight is not emphasized in the previous literature and is important for policy designed to encourage consumers to adopt new technology, especially in cases like CFLs in which the quality of the technology may be improving over time. Second, we examine comparative statics and dynamic simulations to provide some predictions, which we empirically examine with our state-level hybrid vehicle adoption data.

We consider the simplest model that allows for technological adoption with heterogeneous product quality. In each period, consumers choose between product A, based on the existing technology, and products B and C, which use newer technology but differ in quality. In our empirical application, the product A would represent a vehicle with a traditional internal combustion engine and products B and C would represent the Toyota Prius and Honda Insight.

Our model follows a standard discrete choice set-up. We assume that the perceived utility to consumer i of purchasing product $j \in \{A, B, C\}$ is given by:

$$U_{ij}(\Omega_{it}) = \hat{\eta}_j(\Omega_{it}) + \varepsilon_{ij} ,$$

In this framework, $\hat{\eta}_j$ is the consumer's assessment of the mean utility generated by product *j*, and includes both the hedonic utility generated by the product's observable attributes as well as the consumer's assessment of the product's quality or reliability. Finally, ε_{ij} is a mean-zero IID error term with a Type I extreme value distribution that captures consumer *i*'s idiosyncratic preference for product *j*.

The assessment is a function of the set of signals received by the consumer up until time t: Ω_{it}. Information revelation is straightforward. At time $t = 0$, before the introduction of the new technologies, we assume that all consumers know the true quality of product A, η_A, and have common (but potentially biased) assessments of the quality of products B and C, $\hat{\eta}_B(\Omega_0)$ and $\hat{\eta}_C(\Omega_0)$, respectively. In each successive period, each consumer receives information about the true quality of one of the products in the marketplace with a probability proportional to that product's cumulative market share. If a consumer receives a quality signal from product B or C, she updates her prior to the true quality, η_B or η_C, respectively.

Inference occurs when a consumer knows the true quality of either B or C, but not both. In this case, the consumer's assessment of the quality of the unobserved product is a convex combination of her prior and the true quality of the observed product. That is, if a consumer first observes, η_B, at time t, the posterior assessment of the quality of product C changes to:

$$\hat{\eta}_C(\Omega_{it}) = \gamma\eta_B + (1-\gamma)\hat{\eta}_C(\Omega_0)$$

The parameter γ represents the degree to which the consumer's assessment of the quality of one model of the new technology is influenced by observing the other model.

For a given distribution of information sets, say f(Ω_{it}), the market shares of each product at period t could be derived. Due to the nature of information revelation, f(Ω_{it}) is a function of the installed base of each product in each of the previous periods, which we denote by the vector $\mathbf{s}_t = (S_{A,t}, S_{B,t}, S_{C,t}, S_{A,t-1}, S_{B,t-1}, S_{C,t-1}, \ldots)$, where $S_{j,t}$ is the fraction of consumers at time t who own model j. For our purposes, f(Ω_{it}) can be described fully by four possible cases of interest: (1) a consumer has observed neither η_B nor η_C (Ω_0), (2) a consumer has observed η_B, but not η_C (Ω_B), (3) a consumer has observed η_C, but not η_B (Ω_C), and (4) a consumer has observed both η_B and η_C (Ω_{BC}). Given the information structure above, the fraction of consumers at time t in each of the information sets above is given by:

$$\begin{aligned}
&\Pr(\Omega_0 \mid s_t) = \textstyle\prod_{k=1}^{t} S_{A,k};\\
&\Pr(\Omega_B \mid s_t) = \textstyle\prod_{k=1}^{t}(S_{A,k} + S_{B,k}) - \prod_{k=1}^{t}(S_{A,k});\\
&\Pr(\Omega_C \mid s_t) = \textstyle\prod_{k=1}^{t}(S_{A,k} + S_{C,k}) - \prod_{k=1}^{t}(S_{A,k});\\
&\Pr(\Omega_{BC} \mid s_t) = 1 - \Pr(\Omega_0 \mid s_t) - \Pr(\Omega_B \mid s_t) - \Pr(\Omega_C \mid s_t)
\end{aligned}$$

Eventually (as t increases), information about the true qualities of products B and C diffuse and all consumers base decisions on the true qualities of the three products (i.e., $\Pr(\Omega_{BC}|s_t) \rightarrow 1$).

The probability that consumer i purchases vehicle j, conditional on Ω_{it}, is given by the standard multinomial logit expression:

$$\Pr_j \mid \Omega_{it} = \Pr(U_{ij} > U_{ik} \forall k \mid \Omega_{it}) = \frac{\exp(\hat{\eta}_j(\Omega_{it}))}{\sum_k \exp(\hat{\eta}_k(\Omega_{it}))}.$$

the fraction of consumers purchasing good j in period t is given by:

$$\Pr_j(\mathbf{s}_t) = \int_{\Omega_{it}} (\Pr_j \mid \Omega_{it}) f(\Omega_{it} \mid \mathbf{s}_t) d\Omega$$

Given the discrete nature of the distribution of Ω_{it}, this probability can be written as

$$\Pr_j(\mathbf{s}_t) = \sum_{\substack{\Omega\in\{\Omega_0,\Omega_B,\\ \Omega_C,\Omega_{BC}\}}} (\Pr_j \mid \Omega) \Pr(\Omega \mid \mathbf{s}_t)$$

a. Comparative Statics

Before turning to simulations, we briefly discuss the comparative statics of the model with respect to the installed base of product B. The comparative statics emphasize some intuition about how heterogeneous quality among a new technology affects its diffusion and generates our first testable hypothesis: being exposed to a high-quality hybrid makes the subsequent adoption of hybrids more likely, and being exposed to a low-quality hybrid makes it less likely.

We consider a marginal increase in the fleet share of product B in period *t* ($S_{B,t}$). Because the three fleet shares must sum to one in each period we simultaneously model a commensurate decrease in the fleet share of the product C in period *t* ($S_{C,t}$). That is, we consider the effects of a marginal reallocation between the share of product B and product C. Both of these are the new technology (hybrids), so we are considering a marginal change where the total fraction of the fleet that is hybrid is unchanged, but the ratio of the two hybrid models changes. Government policies (such as incentives for hybrid vehicle purchase) often target particular products and may change relative market penetration of new products. Our empirical exercise will focus on similar variation - states that experienced comparable hybrid vehicle adoption in the first several years, but varied as to whether drivers initially preferred the Insight or the Prius.

Taking the derivative of $\Pr_j(\mathbf{s}_t)$ with respect to the market share of product B, we have:

$$\frac{\partial \Pr_j(\boldsymbol{s}_t)}{\partial S_{B,t}} = \frac{\partial \Pr(\Omega_B|\boldsymbol{s}_t)}{\partial S_{B,t}}\left[\left(\Pr_j|\Omega_B\right) - \left(\Pr_j|\Omega_{BC}\right)\right] + \frac{\partial \Pr(\Omega_C|\boldsymbol{s}_t)}{\partial S_{B,t}}\left[\left(\Pr_j|\Omega_C\right) - \left(\Pr_j|\Omega_{BC}\right)\right]$$

Increasing the share of model B at the expense of the share of model C means there is a higher probability of observing just B, rather than both B and C, and a lower probability of observing C, rather than both B and C. Using the equations above for these probabilities and rearranging terms, the derivative can be expressed as:

$$\frac{\partial \Pr_j(\mathbf{s}_t)}{\partial S_{B,t}} = \Pr(\Omega_O \mid s_{t-1})\left[\Pr(j \mid \Omega_B) - \Pr(j \mid \Omega_C)\right] + \Pr(\Omega_B \mid s_{t-1})\left[\Pr(j \mid \Omega_B) - \Pr(j \mid \Omega_{BC})\right]$$
$$+ \Pr(\Omega_C \mid s_{t-1})\left[\Pr(j \mid \Omega_{BC}) - \Pr(j \mid \Omega_C)\right]$$

The first term above represents how the increase in the market share of product B affects the fraction of consumers who have not observed the quality of either B or C at t-1. For these consumers, increasing the market share of product B increases the likelihood that they receive a signal of B's quality and reduces the likelihood that they receive a signal of C's quality. Consequently, the effect on the purchases of product j depends on whether they are more likely to purchase a hybrid if they know B's true quality or C's true quality. The second and third terms capture similar effects on consumers who have only received a signal of B and only received a signal of C, respectively. For the former, increasing the market share of B reduces the likelihood that they learn the true quality of both products. For the latter, increasing the market share of B increases the likelihood that they learn the true quality of both products. The signs of each of these two terms depend on whether or not consumers become more likely or less likely to purchase product j as information about B becomes available.

Several points bear specific mention. First, if consumers make inferences about product quality, a change in the market share of B can indirectly affect adoption of product C. If, for example, product B has lower (higher) quality than product C, increasing the market share of B may slow (speed) the subsequent adoption of product C if consumers infer product C to be comparably low (high) quality to product B. Second, it is important to note that the effect of an increase in the market share of B depends on how much information has already diffused to consumers. If little information has diffused about products B and C, the first term in the expression dominates the latter two. During the early stages of adoption, the effect of encouraging consumers to adopt product B rather than product C on subsequent adoption depends on what consumer posteriors would be if they learn about the quality of B rather than C. As products become established, the effect of stimulating adoption of product B rather than product C will diminish. Eventually, all consumers will learn the true quality of both B and C – at this point, no inferences are made by consumers and increasing the market share of B no longer has an effect.[9]

To make the example more concrete, consider specifically the effect of the marginal changes in $S_{B,t}$ and $S_{C,t}$ on the probability of purchasing the non-hybrid model A. Using the standard logit probabilities and the assumptions about information inference described above, this derivative can be written as

[9] Consumers are risk-neutral and making decisions based only on the mean assessment of quality. An extension to this model could also consider risk-averse consumers, and the fact that a higher market share of hybrids affects both the mean and the uncertainty of consumers' assessments.

$$\frac{\partial \Pr_A(\boldsymbol{s}_t)}{\partial S_{B,t}} = \frac{\partial \Pr(\Omega_B|\boldsymbol{s}_t)}{\partial S_{B,t}}\left[\exp(\eta_A)\, D_{A,B} D_{A,BC}\big(\exp(\eta_C) - \exp\big(\gamma\eta_B + (1-\gamma)\hat{\eta}_C(\Omega_0)\big)\big)\right]$$
$$+ \frac{\partial \Pr(\Omega_C|\boldsymbol{s}_t)}{\partial S_{B,t}}\left[\exp(\eta_A)\, D_{A,C} D_{A,BC}\big(\exp(\eta_B) - \exp\big(\gamma\eta_C + (1-\gamma)\hat{\eta}_B(\Omega_0)\big)\big)\right]$$

The first partial derivative in the expression is positive (in fact it equals $\Pr(\Omega_B|\boldsymbol{s}_{t-1}) + \Pr(\Omega_0|\boldsymbol{s}_{t-1})$); increasing the share of B increases the probability of having information set Ω_B. The expression in the first set of brackets is positive whenever C's true quality exceeds the assessment of C's quality based on only observing B. The second partial derivative in the expression is negative ($-\Pr(\Omega_C|\boldsymbol{s}_{t-1}) - \Pr(\Omega_0|\boldsymbol{s}_{t-1})$), because of the decrease in the share of C. The expression in the second set of brackets is positive whenever B's true quality exceeds the assessment of B's quality based only on observing C. This expression demonstrates how the probability of buying a hybrid of either model ($1 - \Pr_A(\boldsymbol{s}_t)$) can be affected by a change in the distribution of the installed base that leaves the total number of hybrids unchanged but alters the relative share of the two hybrid models. If the hybrid model whose share is increasing (B) has a higher true quality than the quality inferred from the other model, or if the model whose share is decreasing (C) has a lower true quality than the quality inferred from the first model, then this change will increase the overall adoption of hybrids. This is our first testable hypothesis.

b. Simulated Diffusion Curves

We now present some stylized simulations to better illustrate the dynamics of the model. We stress that these simulations are not designed to be as realistic as possible; there are clearly many aspects of the market for hybrids that are not captured here. Rather, the simulations are designed to be as simple as possible while still demonstrating the key intuitions that will be tested in the empirical section.[10] We begin by presenting a simple case with products of heterogeneous quality introduced at the same time where consumers' priors are accurate. We then consider alternative cases in which consumers' priors are inaccurate, and they can infer the quality of one product from the other.

[10] For instance, the market share of hybrids in our simulations is higher than their market share in the US vehicle fleet, in the long run. The observed market share in the fleet as of our data set is so low that the qualitative effects are difficult to see in these simulations.

We present the first case in Figure 1.[11] Figure 1 graphs the diffusion of hybrids, i.e. $S_{B,t} + S_{C,t}$, over time. Because priors are accurate, there is no learning about quality. Rather, the growth in the hybrid share arises because the initial share of hybrids (0%) is lower than the steady-state share (about 33%), and the market takes time to reach equilibrium (about 150 periods).

Figure 2 presents hybrid diffusion curve when learning about quality comes into play. In this simulation, consumers' priors underestimate the true quality of the two hybrid vehicles.[12] Here we observe an S-shaped diffusion curve. Initial adoption is slow – reflecting consumers' priors that both hybrids B and C are of low quality. As consumers begin to adopt the new products, subsequent consumers observe true product quality and are more likely to purchase either hybrid model.

Finally, Figure 3 presents the main qualitative findings of our dynamic model, illustrating the relationship between initial market share and subsequent adoption. Figure 3 presents hybrid diffusion curves for three scenarios in which we assume that hybrids collectively begin with a 30% market share. We then vary product B's and C's fraction of that 30%. In the "Product B intensive start" simulation, B's initial market share is 30%, while in "Product C intensive start," C's initial share is 30%. In "Intermediate start," each has a 15% initial market share. Thus, in each of the three simulations in Figure 3, the total initial hybrid share is 30%, but that 30% is allocated between hybrid B and C in different combinations. All other parameter values are identical to those in Figure 2. We again plot the hybrid diffusion curve ($S_{B,t} + S_{C,t}$) for each simulation.

When consumers infer the qualities of B and C, increasing the initial market share of product C slows subsequent adoption of the new technology. This is because C is the low-quality hybrid. The more exposure that consumers have to the low-quality model, the more likely they are to have beliefs that hybrids overall are of low-quality. In particular, note that for the "Product C intensive start" simulation there is a long period where the hybrid market share is below its initial value, despite the fact that its initial value is already below the steady-state value. This is another demonstration of our first testable hypothesis. The policy implication of

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[11] In this first case, the true qualities of the three models are $\eta_A = 10$, $\eta_B = 9$, and $\eta_C = 8$. The priors for each of these three models are accurate. Initially, the non-hybrid model A has 100% market share ($S_{A,1} = 1$). The inference parameter $\gamma = 0.9$. In each period, 2.5% of consumers purchase a new vehicle. We simulate for 200 periods.

[12] In this case, all of the parameters are the same as in the prior footnote, except that the priors for the hybrid vehicles are lower: $\hat{\eta}_B(\Omega_0) = 7$ and $\hat{\eta}_C(\Omega_0) = 6$.

this result is clear: policies that provide incentives for new technology may actually slow, rather than accelerate, adoption if the policies target the "wrong" model of the new technology. An exogenous increase in the initial installed base of model C, perhaps due to a tax break targeted at model C, would inhibit rather than promote hybrid vehicle adoption.

This effect is necessarily temporary, however, since eventually all consumers' beliefs reach the true values of product quality. In this simulation, by about period 200 the impact of the initial market share is gone. Therefore, the effect of the initial level of total hybrid penetration and the initial relative share of high- and low-quality hybrid models will diminish over time and eventually disappear. This is our second testable hypothesis.

Lastly, the model can be amended to include more than two hybrid models and a conventional alternate. In particular, we consider one specification with three hybrid models, where two of the three come from one manufacturer and the third from a different manufacturer. Here we describe the predictions of this extension; details are available upon request. Suppose that the inference that consumers make from one model to another is stronger if those models are from the same manufacturer than if they are from different manufacturers. For instance, if a consumer only observes model B, then his assessment of model C's quality is

$$\hat{\eta}_C(\Omega_B) = \gamma\eta_B + (1-\gamma)\hat{\eta}_C(\Omega_0).$$

where B and C are models from the same manufacturer. Still only observing B, that consumer's assessment of model D's quality is

$$\hat{\eta}_D(\Omega_B) = \kappa\eta_B + (1-\kappa)\hat{\eta}_C(\Omega_0),$$

where B and D are models from different manufacturers. The quality inference is less strong for a model from a different manufacturer when $\kappa < \gamma$.

When this holds, we show that the diffusion effect from exposure to one model will be larger for hybrids made by the same manufacturer than it will be for hybrids made by other manufacturers. This is our third testable hypothesis.

II. Data and Descriptive Analysis

To test our hypotheses, we use the same data set as Gallagher and Muehlegger (2011). The data set was purchased from JD Power and Associates and is based on proprietary data on consumer purchases of new vehicles. Purchases are aggregated at the quarter-state level for each of eleven hybrid models from 2000 Q1 to 2006 Q4.[13]

The data on hybrid car purchases are combined with a number of control variables. 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. We use League of Conservation Voters scores as a measure for a state's preferences for environmentalism – for each year, we calculate the average of the LCV scores of a state's Senate and House delegations.[14] Quarterly tax-inclusive retail gasoline prices for each state are determined using data from the Energy Information Administration and the Federal Highway Administration. Data on the generosity of state tax incentives for hybrid adoption were collected. These incentives vary substantially across both state and time, and a value for tax incentives at the state-quarter level has been calculated and is used as a control. In addition, the type of the incentive differs substantially across states – approximately one third of the states offering an incentive choose to waive sales taxes, while the remaining two-thirds allow consumers a state tax credit.

While Gallagher and Muehlegger (2011) 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 identify the causal impact of the penetration of a hybrid model in a particular state at the start of period t on hybrid purchases during period t. For each model-state-quarter, we calculate the cumulative total sales of that model from all previous periods.[15] These values of cumulative total sales are divided by the state population in a quarter to create the variable for hybrid model penetration.

Figure 4 shows the diffusion of the two hybrid models that we focus on, 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 market share of the entire hybrid vehicle segment. The growth in hybrid penetration is approximately exponential. In early years,

[13] The models in the data are from Ford (Escape), Honda (Accord, Civic, Insight), Lexus (GS450h, RX400h), Mercury (Mariner), Saturn (VUE), and Toyota (Camry, Highlander, Prius).
[14] Alternative measures for preferences for environmentalism include share of Green Party voters (Kahn 2007) or Sierra Club membership (Gallagher and Muehlegger 2011).
[15] 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.

the market was dominated primarily by the Insight and the Prius. While the Prius has continued to grow, the penetration of Insight sales flattened (the Honda Insight was discontinued in 2006). Consequently, the market share of the Prius rose quickly to approximately 60 percent. As more models were introduced, the market share of the Prius first stabilized and then fell. Different models clearly had qualitatively different patterns of diffusion. Similarly, it may be the case that the penetration rates of different models had different effects on consumer adoption of hybrids.

Our goal is to examine how the stock of Priuses and Insights in a state affects hybrid vehicle adoption. To illustrate the basic comparison, Figure 5 graphs cumulative hybrid vehicle penetration per capita in Insight-intensive states and Prius-intensive states. To control for initial adoption of hybrid vehicles, we group states by cumulative hybrid vehicle penetration at the end of 2001.[16] Effectively, Figure 5 provides a graphical comparison of states with similar hybrid vehicle adoption through the end of 2001 and examines subsequent adoption in states with a relatively high share of Honda Insights. Amongst states with relatively high (but comparable) hybrid vehicle penetration at the end of 2001, subsequent hybrid vehicle ownership grew more quickly in Prius-intensive than in Insight-intensive states.

III. Empirical Approach

Formally, we regress the log of per capita sales of hybrids in state i in period t, y_{it}, on the logs of the cumulative penetration rates of Priuses and Insights, defined as the total sales in state i of Priuses or Insights, respectively, in all periods until period t, divided by state i's population in period t. Call these variables $Prius_{it}$ and $Insight_{it}$. We also include the state-level demographic variables, gasoline prices, and tax incentives, described above, as well as a constant, in X_{it}. As a starting point, we consider the specification:

$$y_{it} = \boldsymbol{\beta X}_{it} + \lambda_P Prius_{it} + \lambda_I Insight_{it} + \varepsilon_{it}. \tag{1}$$

Omitted variables likely bias this specification. Even after controlling for observable characteristics, some states may have unobservable features that lead them to be more likely to prefer hybrids both in the past and in the current quarter, thus upwardly biasing the estimated coefficient. If these unobservable features are correlated with relative preferences for the Insight or Prius, we may attribute differences in consumer willingness to adopt hybrid vehicles to the

[16] As we discuss below, we classify states as Insight-intensive (Prius-intensive) if the cumulative hybrid vehicle market share of the Honda Insight at the end of the 2001 was above (below) the median.

Prius or Insight. Our first strategy against this bias is to include state fixed effects. To the extent that any unobservable feature at the state level is constant over time, this fixed effect will eliminate this bias.[17] We also include time fixed effects, to account for nationwide time-varying changes in preferences for hybrids. This specification is given by equation 2:

$$y_{it} = \boldsymbol{\beta X}_{it} + \lambda_P Prius_{it} + \lambda_I Insight_{it} + \alpha_i + \eta_t + \varepsilon_{it}. \tag{2}$$

Even after including fixed effects, we still worry about bias. We thus turn to instrumental variables estimation. We use two sets of instruments. First, we calculate the difference between per capita Honda registrations in 1999 and per capita Toyota registrations in 1999, one year before hybrid vehicle introduction. Second, we include dummy variables for whether Honda or Toyota has a vehicle assembly plant in a given state. We interact both instruments with time fixed effects to flexibly capture the relationship between pre-hybrid brand preferences and subsequent Prius and Insight adoption. That is, each instrument is allowed to have a different effect on cumulative penetration rates in each quarter.[18]

To be valid, the instruments must be correlated with initial relative sales of Priuses and Insights but not with consumer willingness to adopt hybrid vehicles. Pre-hybrid vehicle registrations are partially determined by the strength of dealership networks and underlying consumer preferences for Honda or Toyota – but importantly are unlikely to be correlated with future consumer willingness to adopt hybrid vehicle technology. It is less clear that the exclusion restriction is satisfied for the second instrument. Although local production is likely correlated with sales by brand, local production may also have a supply effect. In particular, if local production increases local supply of hybrid vehicles, the exclusion restriction would be violated. Fortunately, all Honda and Toyota hybrid vehicles were assembled outside the U.S. during the study period; the instruments are based on plants that build non-hybrid Hondas and Toyotas only. It is therefore unlikely that these instruments have a local supply effect on hybrid vehicle adoption, but they are likely correlated with initial relative preferences for the Prius and Insight.

Formally, we estimate

$$y_{it} = \boldsymbol{\beta X}_{it} + \lambda_P Prius_{it} + \lambda_I Insight_{it} + \alpha_i + \eta_t + \varepsilon_{it} \tag{3}$$

$$Prius_{it} = \boldsymbol{\beta_P X}_{it} + \boldsymbol{\gamma_P Z}_{it} + \alpha p_i + \eta p_t + \varepsilon p_{it} \tag{4}$$

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[17] We later also allow for a state-specific linear time trend.
[18] These data are obtained from Polk.

$$Insight_{it} = \boldsymbol{\beta_I X_{it}} + \boldsymbol{\gamma_I Z_{it}} + \alpha I_i + \eta I_t + \varepsilon I_{it} \tag{5}$$

Equation 3 is the second stage, and we use fitted values of $Prius_{it}$ and $Insight_{it}$. As instruments Z_{it} in the first stage equations 4 and 5, we interact time dummies and the difference in 1999 per capita Honda and Toyota registrations and with dummy variables for the presence of a local Honda and/or Toyota production facility. The assumptions behind this identification strategy are, first, that the γ parameters are non-zero, and, second, that $E(\varepsilon|Z) = 0$.[19]

The IV assumptions with the state fixed effects can be interpreted in terms of demeaned variables. The relevance assumption is that the (demeaned) instruments are significantly correlated with the (demeaned) endogenous variables. For the registration differential instruments, that amounts to the 1999 Honda and Toyota registration difference interacted with time dummies being significantly correlated with the state-demeaned cumulative penetration rates of Priuses and Insights. Likewise, the indicator for a Toyota or Honda assembly plant, interacted with time dummies, must also be correlated with the state-demeaned cumulative penetration rate. The relevance assumption is testable, and it is supported empirically. The exclusion assumption is that the demeaned instruments are uncorrelated with the demeaned dependent variable except through their effect on the demeaned endogenous regressors. In this case, that amounts to the 1999 Honda and Toyota registration differences and the assembly plant location indicators interacted with time dummies not directly influencing the state-demeaned new hybrid sales per capita.[20] With regard to the 1999 registration data, the identification strategy is not identifying off of the idiosyncratic portion of 1999 sales. Rather, 1999 registrations are used as a proxy for unobservables that affect relative Honda-Toyota shares but not overall hybrid demand.

Under what scenario would the exclusion assumption be violated? For our first set of instruments, suppose there is a demand shock for relatively fuel efficient cars in some state in 1999 (say a gasoline tax increase). Toyota and Honda registrations in 1999 will go up, since these cars are relatively fuel efficient. If this demand shock is persistent (say, the tax increase in permanent), then the demand for hybrids cars in future periods will go up as well, since hybrids are relatively fuel efficient. Thus, the instrument directly affects the dependent variable. We are

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[19] Instead of the difference between per capital Honda and Toyota registrations as the instrument, we also tried using the ratio, and using both Honda and Toyota registrations. Results are robust to any of these specifications.

[20] We only use pre-hybrid registration data for one year, 1999. Therefore, interacting these state-level registrations with time indicators is necessary to avoid perfect multicollinearity in the first stage.

confident that this violation of the exclusion assumption is not realized. First, the particular mechanism for the fuel efficiency demand shock is controlled for in our regressions; we have state-quarter level data on net-of-tax gasoline prices. Second, our instruments capture the relative difference in demand between Toyotas and Hondas. Both of these manufacturers' cars are relatively fuel efficient compared to the average car on the road in the US. [21] We do not expect that a fuel economy demand shock would relatively favor one manufacturer over the other, a claim that we could not make if the two manufacturers were, say, Honda and Ford. In other words, we do not attribute the difference between Honda and Toyota registrations in 1999 to fuel demand shocks alone. Instead, we attribute the difference to potentially unobservable factors that affect only relative demands for cars of those two manufacturers, such as the strength of dealership networks and underlying consumer brand preferences.

Next consider our second set of instruments, the indicator variables for Honda or Toyota assembly plants, interacted with time dummies. These are intended to measure state-specific preferences for Hondas or Toyotas. It is possible that an unobservable shock that is correlated with the location of Toyota plants could affect some states' demands for Toyotas. However, we think it unlikely that such a shock would affect those states' demand for hybrids, since none of the Toyota plants (nor the Honda plants) manufacture hybrids. Instead, the shock would likely affect early penetration rates of Insights and Priuses and would have no effect on later overall hybrid penetration rates.

This identification strategy addresses the potential upward bias in coefficient estimates arising from unobserved, time-varying heterogeneity among states in preferences for hybrids. A different issue may cause a downward bias: saturation. When a hybrid model is first introduced in a state, the most hybrid-affine consumers will be the first to purchase one. The remaining consumers are less desirous of hybrids, and so the likelihood of hybrid adoption will decrease. This effect will bias downwards our coefficient on penetration of both hybrid models, assuming the effect applies to both models. This is a conservative bias for our estimates of positive coefficients (as we find for the Prius), but potentially a cause for concern for our negative coefficient estimates (on Insights). Our key findings, however, relate to the difference between

[21] Mean fuel economy (combined) for Toyota and Honda 1999-year models was 24.6 mpg and 24.7 mpg respectively. In contrast, average fuel economy across all makes and models was 21.6 mpg and average fuel economy for models of Chrysler, Ford and GM were 21.5, 19.1 and 16.9, respectively.

the Prius and the Insight coefficient, and it seems unlikely that saturation will affect this difference.

Our IV strategy can be compared to the strategy in Narayanan and Nair (2013). They use two sets of instruments. One is based on the installed-base of flex-fuel cars. The other is based on the market penetration rate of non-Prius hybrids, since their dependent variable is just Prius adoption. The identifying assumption behind this IV strategy is that the contagion effects of hybrids is restricted to just Priuses. According to the assumption, other hybrids, like the Honda Civic hybrid, are visually almost identical to their non-hybrid counterparts, and thus they provide no signal to consumers and have no contagion effects. We find this assumption not applicable for our analysis. In fact, comparing the early models of the Prius and the Insight to comparable non-hybrids (the Camry and the Civic), the Insight was more visually different from a non-hybrid than was the Prius.

Our empirical strategy exploits variation in early penetration rates of the Insight and the Prius across states. Figure 6 provides a scatter plot of cumulative Insight sales versus cumulative Prius sales for the fourth quarter of 2001 (the last period for which these were the only two models available) and for the fourth quarter or 2005 (near the end of our sample period). The values are in total cumulative sales per 1000 population. The scale is not symmetric, so the 45 degree line is drawn in each panel. The first panel shows that, although there is positive correlation between states with high Prius sales and those with high Insight sales, there 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. By 2005, there is still variation between the relative Insight intensity and Prius intensity, although overall all states are much more Prius-intensive (all points lying well above the 45 degree line). Figure 7 presents further evidence of variation in early penetration rates of the Insight and the Prius. Figure 7 presents two histograms of the number of Insights as a percentage of total cumulative hybrid sales by state, at the end of 2001 and at the end of 2005. In 2001 Q4, the Insight's hybrid market share ranged from 0% (in DC) to 59.2% (in Louisiana). By the end of 2005, the highest Insight market share in any state is in Ohio, with 12.4%.

Table 1 presents summary statistics comparing “Insight-intensive” states (where the Insight’s share of hybrid vehicle sales in 2001 Q4 was above the median of 39.9%) to “Prius-intensive" states (with below-median Insight market shares). On average, Prius-intensive states have higher tax-inclusive gasoline prices, offer more generous incentives, are slightly wealthier and have representatives who vote more liberally on environmental issues. Furthermore, cumulative hybrid vehicle adoption as of 2001 Q4 is slightly higher in these states – although much of this difference arises from California, where over 6,000 hybrid vehicles were sold in 2000 and 2001. Excluding California, cumulative hybrid vehicle adoption in Prius-intensive states averaged 450 vehicles. The pattern of the instrumental variables (new Honda and Toyota registrations per capita in 1999) does not align with our priors: the ratio of Toyota to Honda registrations in 1999 is slightly higher for Insight-intensive states. In all cases, though, the distributions overlap substantially and the differences are not statistically significant.

IV. Results

IV. 1. Are initial market shares correlated with subsequent adoption?

We first test to see if initial Prius and Insight adoption is correlated with subsequent hybrid vehicle purchases. Our first testable hypothesis predicts that if the Prius was perceived to be of high-quality compared to prior beliefs, then Prius sales should have a positive effect on subsequent hybrid vehicle purchases. Similarly, if the Insight was perceived to be of low-quality compared to the prior, Insight purchases should have a negative effect on subsequent hybrid vehicle penetration.

The base case regression results are presented in Table 2. We present eight specifications, four OLS and four with our instrumental variables approach. For each strategy, we present results without state or time fixed effects (columns 1 and 5), with state fixed effects (columns 2 and 6), and with state and time fixed effects (columns 3, 4, 5, and 7). The regressions in columns 4 and 8 correct for first-order autocorrelation using Prais-Winsten estimation, allowing the coefficient of the AR(1) process specific to each panel. In all specifications, all of the state-quarter level demographic data, gasoline prices and tax-incentive data are included. [22]

[22] First-stage IV results are presented in Appendix Table 1. The coefficients on the Honda/Toyota registration differential instruments (interacted with time indicators) are negative in both the Prius and the Insight first stage regressions, indicating that states with relatively more Honda than Toyota registrations in 1999 had lower adoption of both types of hybrids. However, the magnitudes of the negative coefficients are greater on the Prius regressions than on the Insight regressions, suggesting that our instruments are correctly predicting relative Prius and Insight market shares. The coefficients on the assembly plant location indicators are generally insignificant in the Insight

Table 2 demonstrates how different models can impart different signals about unknown hybrid quality and thus lead to different diffusion rates. In all columns, the coefficient on the log of the Prius penetration rate is significantly positive, with an estimated elasticity between 0.30 and 0.55. The coefficient on the log of the Insight penetration rate is negative in all columns that include state-fixed effects, ranging from –0.14 to –0.44, although it is not always statistically significant. Some of the demographic and incentive variables also impact hybrid vehicle sales. States with higher income residents and with younger residents tend to have higher hybrid sales. Higher hybrid sales are also associated with higher gasoline prices and higher values of tax incentives for hybrid purchases, reinforcing results found in Gallagher and Muehlegger (2011) and Beresteanu and Li (2011). Curiously, a higher score for a congressional delegation by the League of Conservation Voters, indicating a more environmentally-friendly voting record, is associated with a lower propensity to buy hybrids. The effect is small but significant.

The results from Table 2 are consistent with the first testable hypotheses from our theory as well as anecdotal evidence from model sales and from stories in the media about the relative quality of these two models. The Prius appears to have provided a positive signal – initial Prius sales are positively correlated with subsequent hybrid vehicle adoption. In addition, we find some evidence, though not as statistically significant, that suggests the Insight provided a negative signal of hybrid quality. 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 recently redesigned. 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

regression, but in the Prius regression, the Toyota plant indicators have positive coefficients and the Honda plant indicators have negative coefficients, as we would expect. F-tests on the joint significance of the instruments in the first stage are significant at the 1% level for both Prius and Insight penetration rates, and they are well above the conventional bound of 10 indicating weak instruments. The instruments pass a Sargan test of overidentifying restriction (p-value = .7088) when state and time fixed effects are included.

"barely tolerable." Also, the Insight's design, compared to the more conventional Prius, may have contributed to its negative reception (Patton 2007).[23]

In Table 3 we present results from a falsification test. Instead of per-capita hybrid sales (in logs) as the left-hand-side variable, we run regressions where the left-hand-side variable is per-capita sales (in logs) of non-hybrid vehicles. We expect that the right-hand-side variables of interest, the penetration rates of Insights and Priuses, will not affect sales of non-hybrids. This is confirmed in Table 3. In the first column the dependent variable is non-hybrid Honda sales, and in the second column it is non-hybrid Toyota sales. These regressions use the same set of instruments as the regressions in columns 5-8 of Table 2. In neither column is the correlation between Prius or Insight penetration and non-hybrid sales significant.

IV. 2. Does the signaling effect of the initial mix of hybrid vehicles diminish over time?

Our second testable hypothesis predicts that the effect of the initial exposure of hybrid vehicles in a state will diminish as more hybrids enter the market and consumers observe the quality of multiple models. To test this prediction, we compare hybrid vehicle adoption in states with high Prius market share ("Prius-intensive") and states with high Insight market share ("Insight-intensive") at the end of 2001. We choose 2001 Q4 since by this time both Priuses and Insights were differentially allocated across states (see Figure 7) but no other models were yet introduced. The median hybrid market share of Insights across states in 2001 Q4 is 0.399.

We regress the log of the cumulative hybrid sales per capita on cumulative, demeaned values of our dependent variables, and time fixed effects. To test the prediction, we include the interaction between time fixed effects and a dummy variable categorizing states above and below the median Insight market share in the fourth quarter of 2001. The coefficient on these variables reflects cumulative sales in states with an initially high mix of Honda Insights.

$$Log(CumulativeSalesPerCapita_{it}) = \alpha + \beta Cumulative(X_{it}) + \eta_t + \lambda_t * HighInsightPenetration(Q4\text{-}2001) + \varepsilon_{it}, \quad (6)$$

Table 4 presents our estimates. Column 1 reports the OLS estimates, while columns 2 reports the IV estimates using the same set of instruments as the regressions in Table 2 Both

[23] In early model years, the Prius's design looked very similar to its non-hybrid equivalent; only in later model years (2003 and later) did the Prius have a distinctive design. The Insight, by contrast, was distinctive from the start. Sexton and Sexton (2012) argue that the Prius's unique design offered its owners a status bonus relative to the Civic hybrid; their data are from more recent model years in which the Prius was redesigned.

regressions also include time fixed effects, and the cumulative, demeaned values of hybrid incentives (gasoline price, tax incentives and HOV lane access).

In both specifications, we find a pattern consistent with slower hybrid vehicle adoption in Insight-intensive states, though it is only significantly different from zero in the OLS regressions. Hybrid penetration is initially (t=4) 0.451 log points lower in Insight-intensive states than it is in Prius-intensive states. This difference increases until period t=10 (2002Q1). Thereafter, the difference begins to diminish; by the end of the 2006, hybrid penetration is only 0.235 log points lower in Insight-intensive states. The trough in the parameter values occurs in 2005Q4 for the IV regressions, and there is not much evidence of the sales in Insight-intensive states catching up.

Figure 8 plots the coefficient values from the two regressions. Both show a similar pattern, although the effect is estimated less precisely after instrumenting for Insight market share. Consistent with slower hybrid vehicle adoption in Insight-intensive states, the effect increases during the first two years of the sample. The trend reverses in the OLS estimates – the differential gradually rising after 2002. After instrumenting, the effect is more modest as is the change in trend. After 2002Q4, the trend in the IV estimates remains flat.

The empirical persistence patterns displayed in Figure 8 are consistent with the predictions of the dynamic model, which suggest that the effect of exposure to a low-quality signal hybrid diminishes over time. Similarly, the results in Figure 8 suggest that the negative effect of an initially high ratio of Insights to Priuses peaks after two to three years, though it does not completely dissipate even after six years.[24]

IV. 3. Does the correlation differ by model or by manufacturer?

If consumers believe that the quality of Toyota hybrids are correlated due to perhaps similar technology, then our third testable hypothesis predicts that a high quality signal from a Prius will be stronger for other Toyota models than for models of other manufacturers, and stronger yet for other Priuses. Similarly, a low quality signal from an Insight may have a stronger negative effect on other Honda models than on models of other manufacturers. We test this prediction in Table 5. In previous regressions, hybrid sales for different models are

[24] These regression results do not include state-fixed effects. When including those in the regressions, the U-shape for the OLS coefficients is even more pronounced, while the Coefficients in the IV regressions are monotone decreasing.

aggregated to total sales at the state-quarter level. In Table 5 the regressions are run at the state-quarter-model level, to allow the impacts of Prius and Insight penetration rates to vary by model and manufacturer. The dependent variable is the log of per capita sales of one hybrid model in a state in a quarter. The right-hand-side variables of interest are the cumulate Prius and Insight penetration rates. We include interaction terms to allow the coefficients on these variables to be different for the same vehicle (i.e. the effect of Prius penetration rates on Prius sales and the effect of Insight penetration rates on Insight sales), for other vehicles of the same manufacturer (e.g. the effect of Prius penetration rates on Toyota Camry sales), and for vehicles by other manufacturers (e.g. the effect of Prius penetration rates on Honda sales). The first coefficient in each column, labeled "Prius on Prius," is the effect of the Prius penetration rate on Prius adoption. The second coefficient, labeled "Prius on other Toyotas," is the effect of the Prius penetration rate on adoption of other Toyota hybrids besides the Prius, and so on. Both columns are OLS regressions with fixed effects. Column 1's errors are clustered at the state-quarter level, while column 2 allows an AR(1) error term. All of the controls from Table 2's regressions are included in each regression here but not reported. We do not use our instrumental variables strategy for these regressions, since the exclusion restriction will not be satisfied when the regression is at the state-quarter-model level.[25] But, we can and do include a richer set of fixed effects to control for unobservable heterogeneity. These regressions include state-model and model-time fixed effects, rather than just state and time fixed effects. Still, the results in Table 5 are not from IV regressions, and the bias from a lagged dependent variable remains, so these results should be interpreted with that caveat in mind.

All of the coefficients show positive diffusion effects from the Prius and negative diffusion effects from the Insight, as consistent with all previous results. The magnitude and the significance of the results present some interesting patterns. The coefficient with the greatest magnitude and highest level of significance is always the one from the same vehicle. Prius penetration rates have a larger positive impact on Prius sales than on sales of any other models, and Insight penetration rates have a larger negative impact on Insight sales than on sales of any other models. For Insights, in fact, the "Insight on Insight" coefficient is the only significant

[25] In the regressions at the state-year level, the restriction assumption is that the pre-hybrid Honda and Toyota per capita registrations do not directly affect total hybrid sales. Here, in the regressions at the state-model-year level, the assumption would be that these pre-hybrid registrations do not directly affect the sales of any particular hybrid model. This assumption does not seem credible, since Toyota registrations should directly affect, say, Camry sales.

coefficient, suggesting that the Insight's negative signal is largely confined to other Insights. For Priuses, the coefficients from other vehicles are consistent with the signaling model where a stronger signal comes from a model by the same manufacturer than by a model from a different manufacturer. However, while the point estimate of the coefficient on "Prius on other Toyotas" is larger than that on "Prius on non-Toyotas," only the latter is significantly different from zero, and they are not significantly different from each other. For Insights, neither of the second two coefficients is significantly different from zero. Thus, we can reject the null hypothesis that signal strength does not vary by model. We cannot reject the null hypothesis that signal strength does not vary by manufacturer. These results define manufacturer by marque, treating marques owned by the same firm (e.g. Toyota and Lexus) as different manufacturers. Treating different marques owned by the same firm as the same manufacturer yields qualitatively similar results. Furthermore, strength of signal may differ not only by manufacturer but also by other features of the car. For example, Toyota and Honda have fundamentally different hybrid technologies. The technology used by Ford (and its marque Mercury) is nearly identical to that used by Toyota (the two companies entered a patent-sharing accord in 2004). We replicate Table 5's, grouping models together by engine type instead of by manufacturer. We again reach qualitatively the same results: significant "same vehicle" coefficients for both Priuses (positive) and Insights (negative), and smaller and less significant "other vehicle, same engine type" and "other engine type" coefficients for both models.

IV. 4. Robustness checks

Table 6 investigates the robustness of the results. In column 1, we regress at the state-quarter-model level instead of the state-quarter level, as we did in Table 5. This regression includes state-model fixed effects and model-quarter fixed effects. Thus, as different models have different national trends (e.g. Prius sales take off and Insight sales sink), these dummy interaction variables allow for any such model-specific pattern. Furthermore, different states are allowed different preferences for individual models, not just for hybrids overall, via the state-model fixed effect. However, this regression does not use instrumental variables, for reasons described above. We again see a positive, significant coefficient on Prius penetration. The coefficient on Insight penetration is negative and significant, but smaller in absolute value than in previous regressions.

The state-fixed effect in our main set of regressions allows for each state to have a different level of per capita hybrid sales. In addition to the peer effects that are the main focus of this paper and the effects from the demographic controls, there may be other differences between states not picked up by merely allowing for alternate intercepts. In particular, different states could have different diffusion curves, in addition to different intercepts. In columns 2 and 3 of Table 6, we allow for more heterogeneity in states' diffusion curves by including a linear state-specific time trend in addition to a state-fixed effect. Thus, not only do different states have different preferences for hybrids, but these preferences are allowed to vary linearly over time at different rates. We identify a diffusion effect off of the deviation from this state-level linear trend. Both columns use our IV strategy, and column 3 also corrects for first-degree autocorrelation. We again see a positive and significant Prius effect. The Insight effect is significantly negative in column 3 but not distinguishable from zero in column 2.

We have chosen to include only Prius and Insight penetration levels on the right-hand-side of the regression equations because they were the first two models introduced and dominated the market for the first three years of the sample. Thus, we believe that any signaling effect from seeing hybrids would come from these models. Nine other hybrid models are present in our sample, and in theory we could put any combination of these models on the right hand side. For almost all other models, though, their late introduction and small representation among states mean that there is insufficient power in the regressions to identify any effect. The only exception may be the Honda Civic hybrid. It was introduced in 2002 Q1, the third year of our sample. By 2003 Q1, its market share of new sales was 49.9%. Columns 4 and 5 thus replicate the fixed effect IV regressions including the log of Civic penetration as an endogenous regressor. The set of instruments is the same as in Table 2's regression; column 5 corrects for autocorrelation. The coefficient on Civic penetration is not significantly different from zero. The Prius coefficient is still positive and significant. The Insight coefficient is again indistinguishable from zero if we do not correct for autocorrelation, and it is significantly negative once we do. Overall, the robustness checks in Table 6 corroborate our main findings of a positive diffusion effect from Priuses. The evidence of a diffusion effect from Insights is mixed, with some specifications finding a negative effect and others unable to reject a zero effect.

V. Conclusion

We have presented a model of technology diffusion showing how learning and heterogeneity in the perceived quality of the technology can affect consumers' decisions. Observation of the technology by consumers provides signals of quality and affects consumers' assessments of the technology. The introduction of models with perceived low quality, relative to consumers' priors, inhibits rather than promotes diffusion. Therefore, incentives to promote the technology's diffusion may instead have the opposite effect, if they propagate low-quality signals.

Using data on state-level sales of new hybrid models, we showed that the diffusion patterns of hybrids are consistent with this peer effects model. Higher penetration rates of the Toyota Prius are associated with higher per-capita sales of hybrid models; penetration rates of the Honda Insight have a negative effect on sales of new hybrids. The negative diffusion effect from the Insight appears to be confined to the Insight, while the positive effect from the Prius spills over to other hybrid models, though with a smaller magnitude than its effect on Priuses. Consistent with our theoretical predictions, we find that the effect of initial adoption decisions diminishes over time. Although we estimate that the effect of the initial vehicle mix peaks after about one to two years and declines thereafter, the effect persists until the end of our sample (six years), suggesting that policies promoting technology adoption may have long-lasting effects.

Our identification strategy exploits variation in early penetration rates of the Prius and the Insight across states. This variation is substantial, as evinced in Figures 6 and 7, but it is not random. The unobserved factors that cause this variation in initial penetration rates may also affect subsequent hybrid adoption, biasing coefficient estimates. We employ instrumental variables to identify a causal installed-base effect. We instrument for the installed base of Priuses and Insights using the relative distribution of non-hybrid Toyota and Honda models and the location of Toyota and Honda manufacturing plants.

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 technological uncertainty and learning 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 these diffusion patterns, though the competing explanations seem less able to account for the persistence results and model- and manufacturer-specific effects seen in Tables 4 and 5. A useful extension to this paper would be to use additional data to attempt to separate these effects.[26] Alternate extensions would be to explicitly model firm behavior, or to use a structural rather than a reduced-form estimation strategy.

Although we do not explicitly model policy in this paper, the implications of our results for policy are clear. While incentives for new technologies, like tax breaks for hybrid cars, are intended to accelerate the technologies' adoption, they may instead inhibit adoption if the incentives are reducing consumers' assessments of the technologies' quality. Of course, it is difficult for policymakers to determine when an incentive may retard rather than accelerate technology adoption, so these incentives should be used with caution.

Our paper's results are relevant for government policy affecting hybrid cars as well as other "clean" technologies more generally. These policies are typically justified for two reasons – the negative externality from emissions or the positive spillover externality from technology adoption. Some previous work has cast doubt on the first justification, finding that the costs of reducing emissions from hybrid vehicle subsidies are too high to justify such policies (Chandra et al. 2010). Our results are a cautionary tale regarding the second justification, since government policy designed to encourage hybrid sales may have the opposite effect if targeted at a low-quality-signal model.

Although our paper focuses on hybrid vehicle adoption, our findings are relevant to other technology policies designed to encourage low-carbon consumer technologies, such as plug-in hybrid cars, electric cars, or home electrical smart meters, as well as firm-level technologies such as carbon capture and storage or renewable energy sources for electric utilities.[27] If the economy is still at the convex portion of an S-shaped diffusion curve, then providing incentives for technology adoption will increase the rate of adoption and the rate of diffusion of the new technology. If interacting with adopters increases the rate of adoption amongst non-adopters, even a short-run incentive may have a substantial impact on the penetration of a new technology.

[26] Choi (1997) provides a theoretical model that includes both informational spillovers and network externalities.
[27] As an example, the Energy Improvement and Extension Act, passed into law October 2008, provides tax credits for plug-in hybrid purchases up to $7,500. The model could also apply to other new types of automobiles besides hybrids, for instance crossovers or minivans.

However, this argument disregards the possibility that competing versions of a new technology may vary in quality, reliability, or other dimensions. Low-quality models of new technology (or models that send low-quality signals) may lower consumers' assessments of quality and, hence, dissuade non-adopters from purchasing the new technology. Consequently, subsidies targeting low-quality models (or first-generation models of a new technology) may slow rather than speed diffusion.

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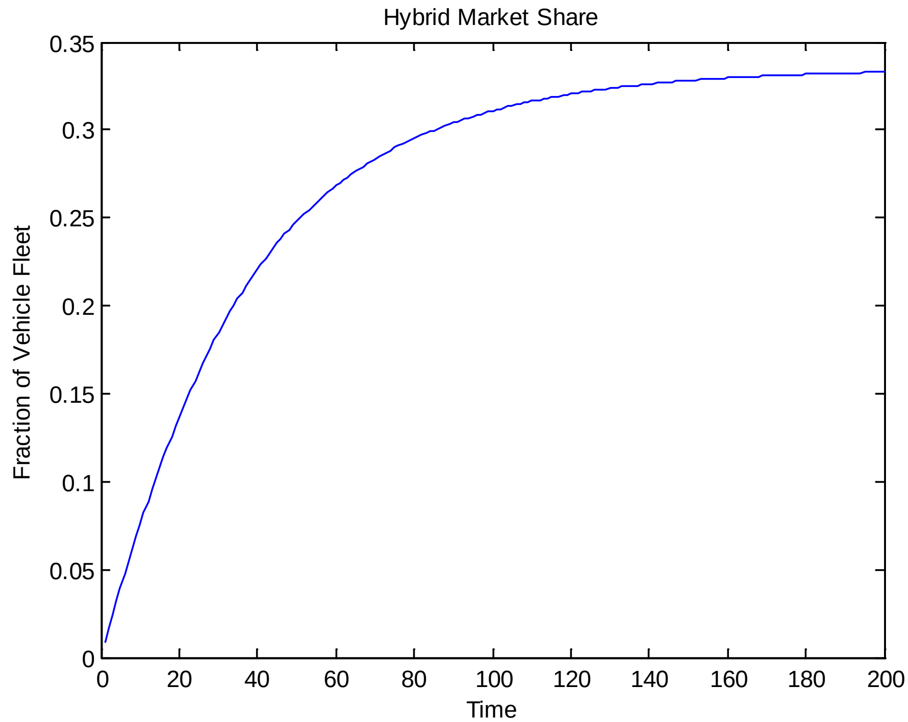
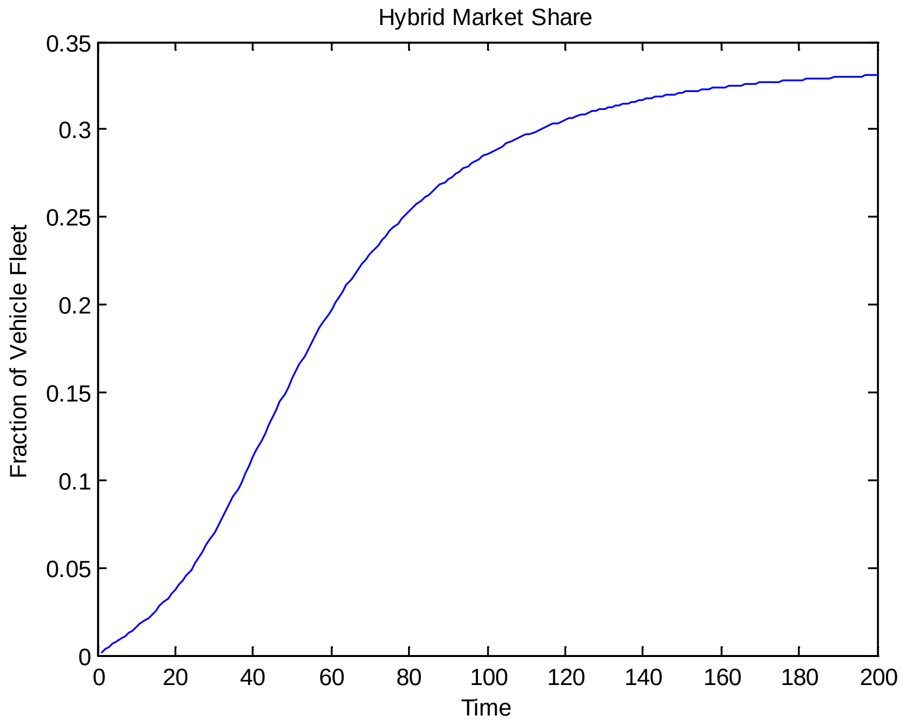
<u>Figure 1 : Hybrid Diffusion Simulation – Accurate Priors</u>



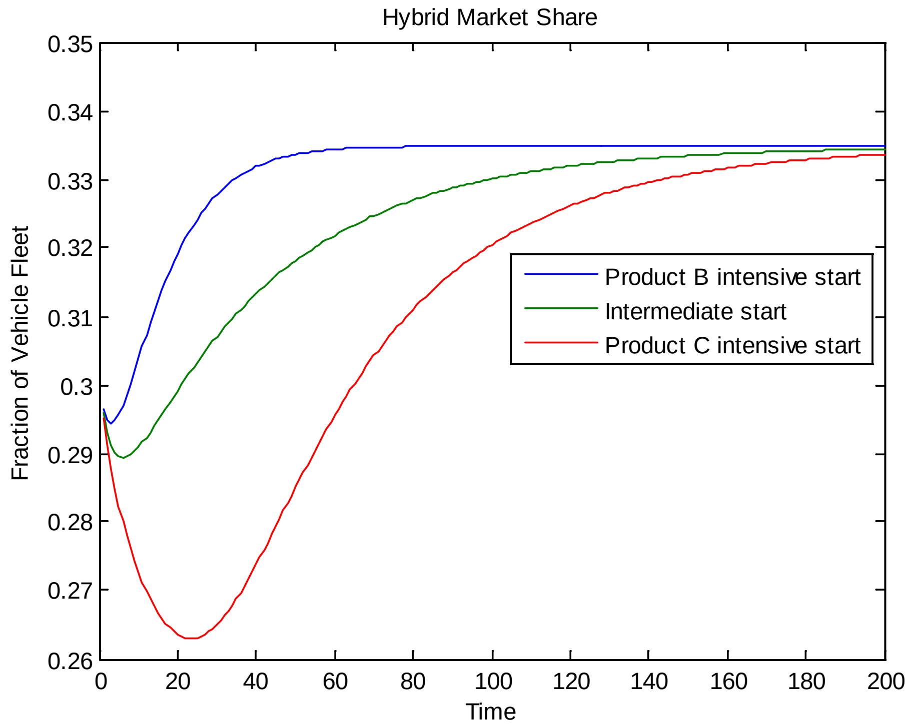
Note: This simulation assumes that products B and C vary in quality and consumers have accurate priors of their qualities. The parameter values are described in the text.

Figure 2 : Hybrid Diffusion Simulation – Inaccurate Priors



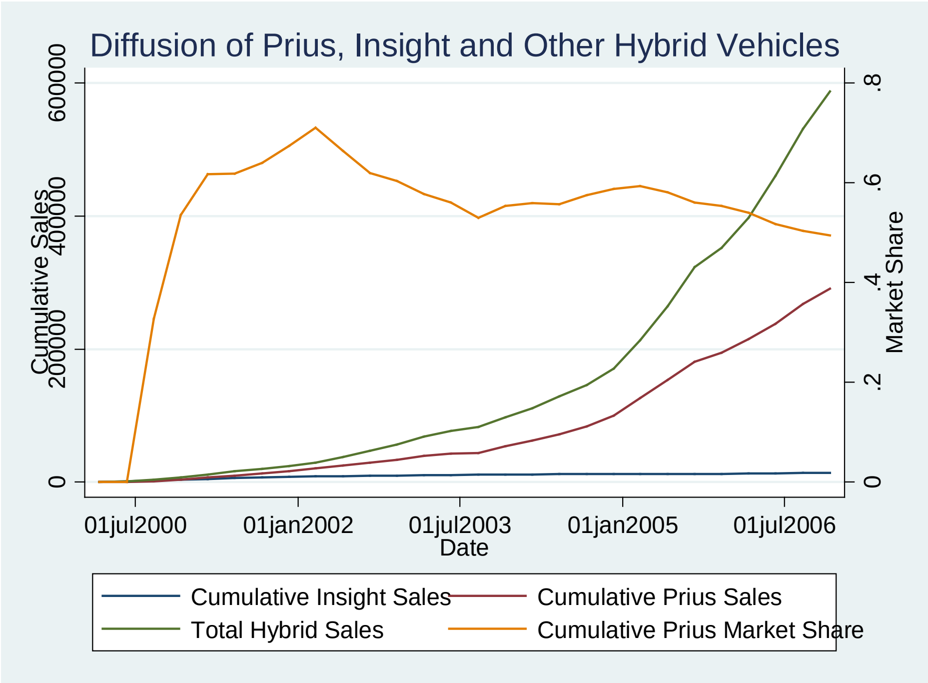
Note: This simulation assumes that products B and C vary in quality, and consumers' priors underestimate the quality of both products B and C. The parameter values are described in the text.

Figure 3 : Hybrid Diffusion Simulations – Different Initial Market Shares



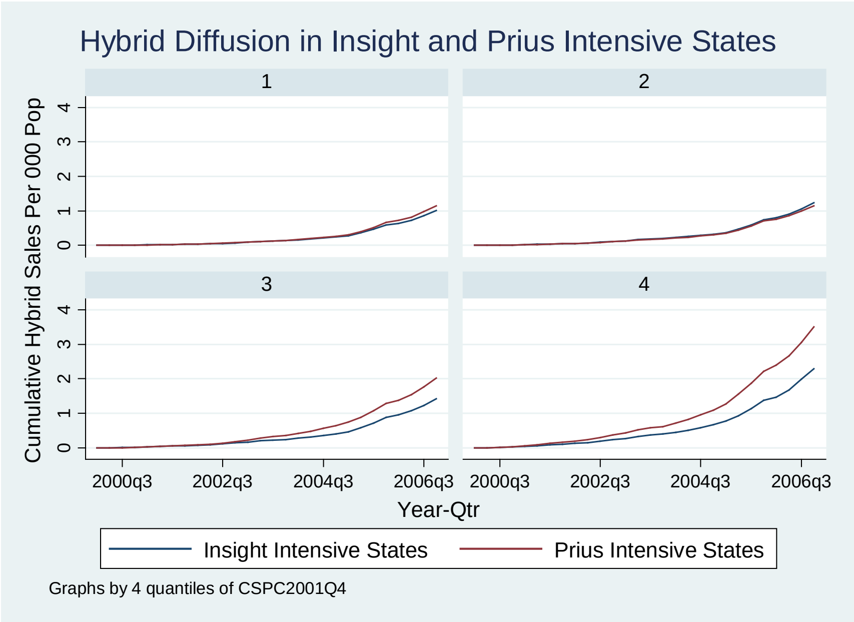
Note: These simulations assume that products B and C vary in quality, and consumers' priors underestimate the quality of both products B and C. The parameter values are described in the text. The intensive starts assume that product B or C starts with a 30% market share. The intermediate start assumes that product B and C each start with a 15% market share.

Figure 4



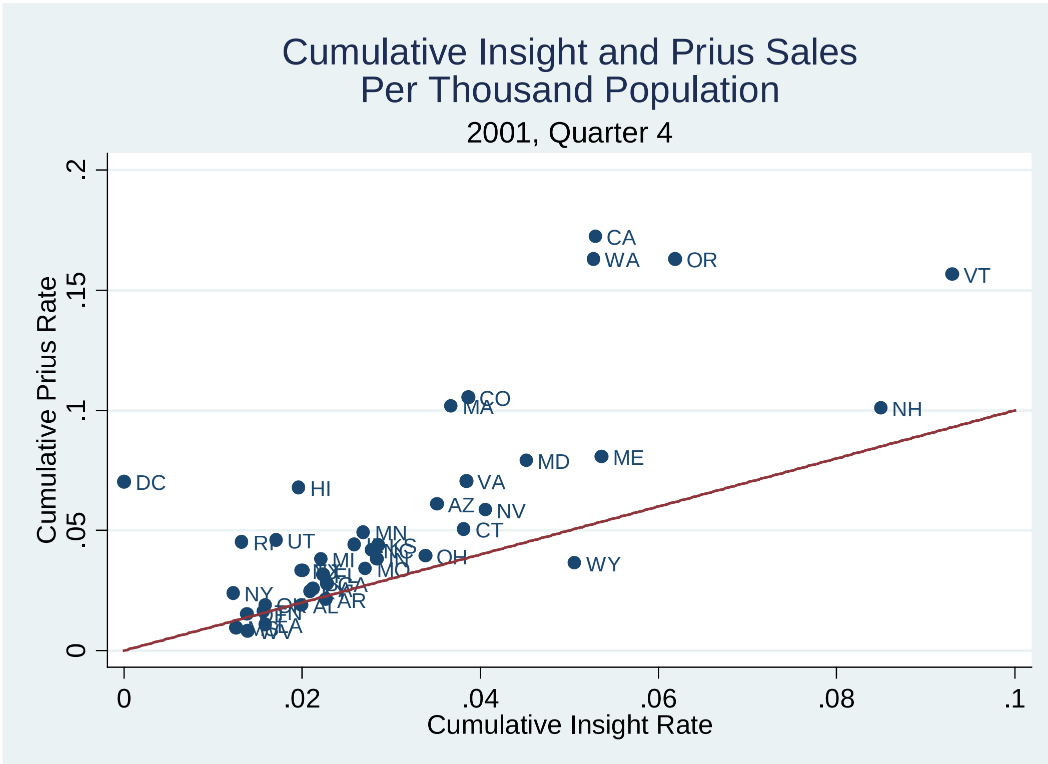
Notes Cumulative sales of Insights, Priuses, and all hybrids in the United States are plotted on the primary y-axis. Cumulative Prius sales as a fraction of cumulative hybrid sales are plotted on the secondary y-axis.

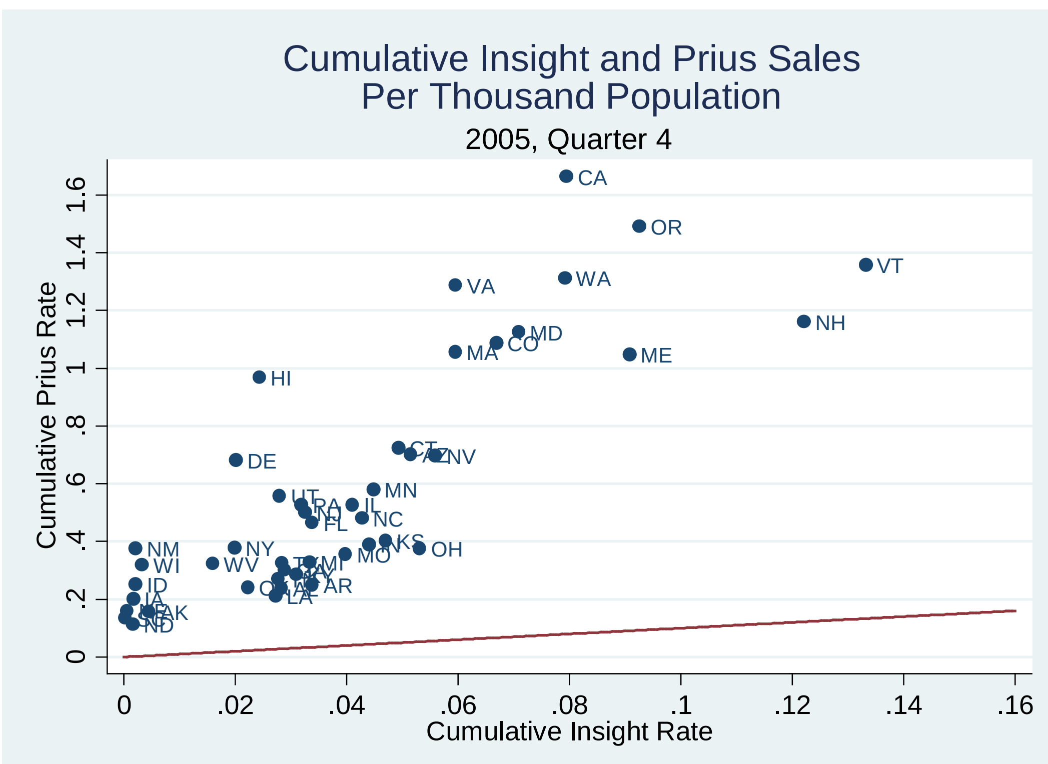
Figure 5



Notes: Insight-intensive (Prius-intensive) states are states that have an above (below) median market share for the Honda Insight in Q4-2001. The four graphs represent the states in the four quartiles of hybrid vehicle penetration in Q4-2001.

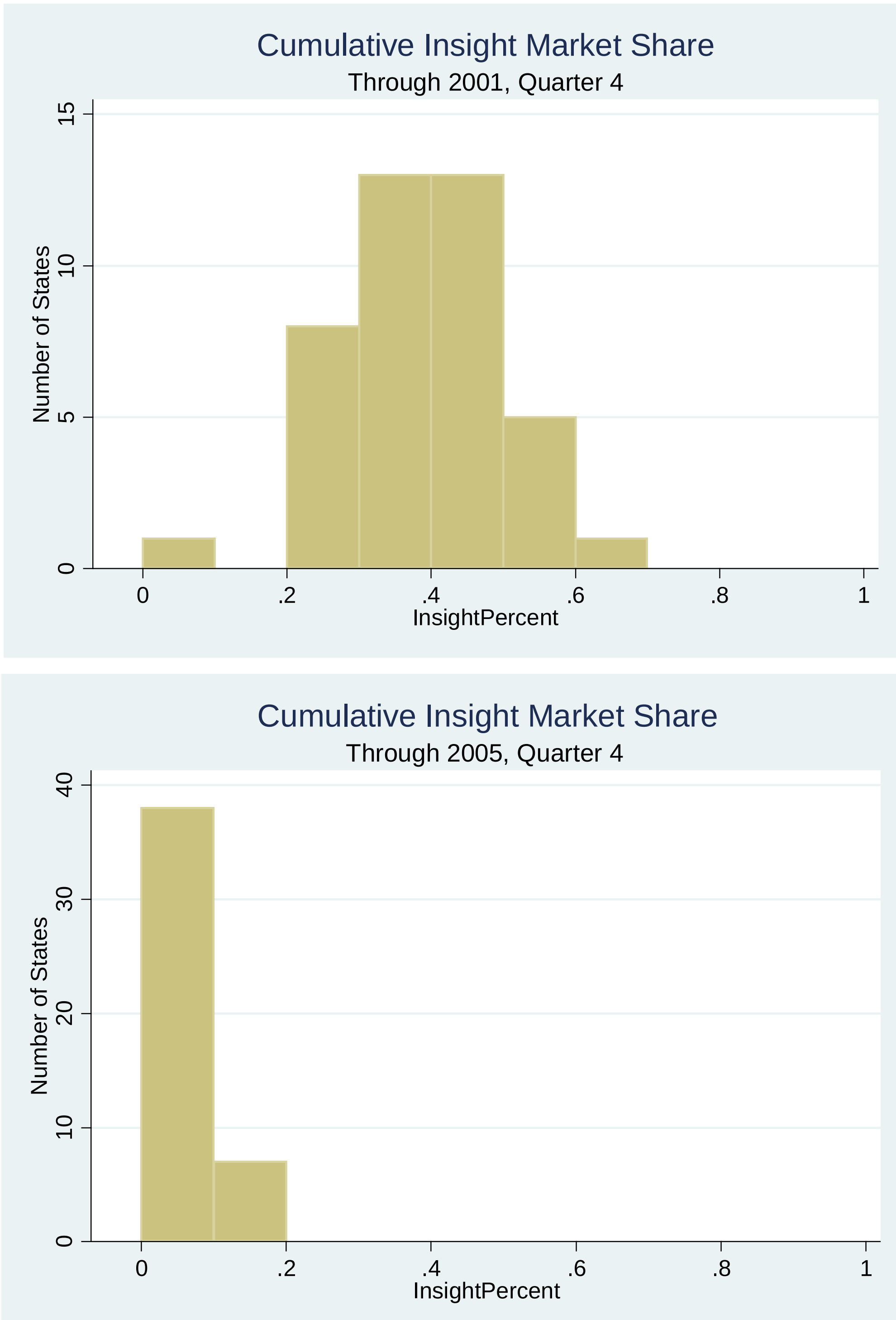
Figure 6





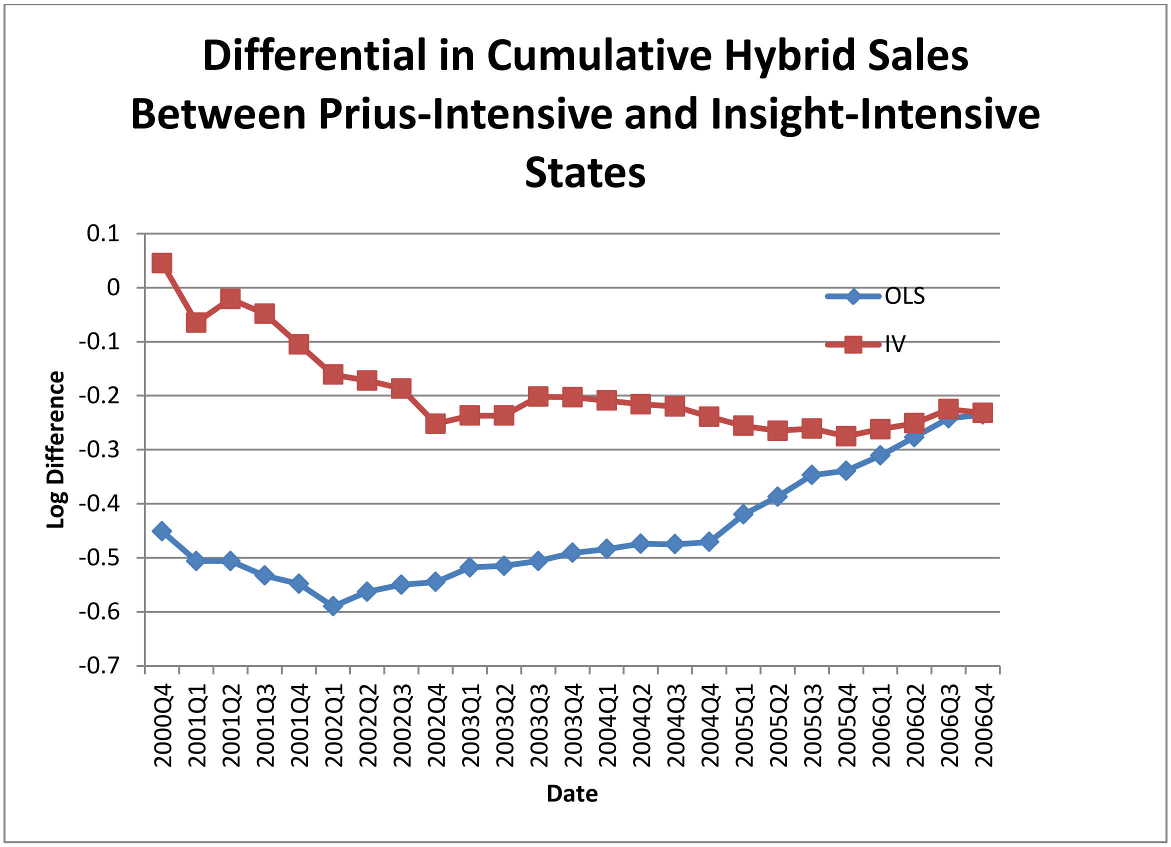
Notes: Cumulative penetration rates are defined as total model sales through the indicated period (2001 Q4 or 2005 Q4) divided by population in thousands in that period. The red line represents the 45 degree line equating Insight and Prius penetration rates.

Figure 7



Notes: The *x*-axis bins represent cumulative Insight market share (as a fraction of all hybrid sales) in a state through the indicated period (2001 Q4 or 2005 Q4).

Figure 8



Note: This figure plots the estimated coefficients on the interaction terms between the time indicator and the indicator variable for Insight-intensive state, from the regressions presented in Table 4, columns 1 and 2. Insight-intensive states are defined by having an Insight market share greater than the median value (39.9%) in 2001 Q4.

Table 1: Summary Statistics for "Insight-Intensive" and "Prius-Intensive" States, 2001 Q4

	Insight-Intensive (20 states)		Prius-Intensive (21 states)	
Variable	Mean	SD	Mean	SD
Tax Inclusive Retail Gasoline Price (cpg)	114.27	8.10	122.94	11.51
State Hybrid Incentive ($000)	0.09	0.40	0.25	0.59
Per Capita Income ($000)	28.24	4.66	32.11	4.81
HS Graduation Rate	0.84	0.04	0.86	0.04
BA Attainment Rate	0.23	0.04	0.29	0.04
Population (millions)	5.30	4.18	7.56	8.36
Mean Age	36.45	1.20	35.82	1.59
Percent Female	0.51	0.01	0.51	0.01
Per Capita Vehicle Miles Travelled (000s miles/year)	11.07	2.09	9.58	1.89
Senate League of Conservation Voters Score	36.25	32.33	58.00	38.52
House League of Conservation Voters Score	34.55	22.23	62.05	27.53
New Honda Registrations (1999)	16613.45	16481.27	26935.62	37060.85
New Toyota Registrations (1999)	21748.45	22627.06	33759.52	50571.71
New Honda Registrations Per Thousand Pop(1999)	2.85	1.02	3.30	0.95
New Toyota Registrations Per Thousand Pop (1999)	3.89	1.29	4.17	1.43
Cumulative Hybrid Sales (as of Q4-2001)	247.55	217.56	707.57	1311.77
Cumulative Hybrid Sales Per Capita (per/1000)	0.05	0.03	0.09	0.05

Notes: "Insight-intensive" states are those whose share of hybrid vehicle sales in 2001 Q4 is above the median share of 39.9%; "Prius-intensive" states are all others in the sample as of 2001 Q4.

Table 2: Hybrid Vehicle Adoption

	OLS				IV			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Prius Penetration	0.453***	0.389***	0.456***	0.338***	0.304**	0.381***	0.553***	0.325***
	(0.071)	(0.057)	(0.104)	(0.040)	(0.123)	(0.052)	(0.180)	(0.047)
Log Insight Penetration	0.078	-0.153*	-0.141*	-0.135***	0.195	-0.154	-0.216	-0.435***
	(0.130)	(0.086)	(0.073)	(0.038)	(0.327)	(0.100)	(0.197)	(0.050)
Log Per Capita Income	3.073**	2.928***	1.078	0.934***	3.161*	2.989**	0.854	0.382
	(1.503)	(1.078)	(0.666)	(0.271)	(1.572)	(1.134)	(0.750)	(0.404)
Mean Age	-4.590	1.538	-17.940***	-19.760***	-4.061	2.318	-17.131***	-27.422***
	(5.066)	(5.415)	(4.287)	(2.263)	(4.842)	(5.600)	(3.955)	(1.492)
Percent Female	6.667	10.558	21.810	-1.598	4.608	9.695	20.512	-2.124
	(12.279)	(23.850)	(17.696)	(8.601)	(12.289)	(24.681)	(16.238)	(7.787)
HS Grad Percent	-9.199**	2.304	1.675	2.309***	-9.457**	2.305	1.735*	0.710
	(4.362)	(1.561)	(1.073)	(0.563)	(4.399)	(1.552)	(1.015)	(0.605)
Percent of Adults with BA	0.837	-0.375	-0.237	-0.574***	0.980	-0.374	-0.167	-0.187
	(1.157)	(0.358)	(0.266)	(0.155)	(1.165)	(0.374)	(0.265)	(0.151)
LCV Score	-0.005	-0.005***	-0.003**	-0.002***	-0.005	-0.005***	-0.003**	-0.002**
	(0.006)	(0.002)	(0.001)	(0.001)	(0.006)	(0.002)	(0.001)	(0.001)
Log Retail Gasoline Price	1.144***	1.370***	0.629	0.415*	1.687***	1.364***	0.595	0.764***
	(0.258)	(0.165)	(0.414)	(0.217)	(0.494)	(0.156)	(0.431)	(0.263)
Log Tax Incentives	0.034	0.097	0.107	0.130***	0.037	0.099*	0.115	0.108***
	(0.151)	(0.060)	(0.066)	(0.030)	(0.151)	(0.059)	(0.072)	(0.031)
HOV lane access	0.209	0.022	0.073	0.005	0.280	0.025	0.075	0.061
	(0.381)	(0.084)	(0.084)	(0.052)	(0.364)	(0.084)	(0.079)	(0.044)
Observations	1024	1024	1024	1024	1024	1024	1024	1190
R-squared	0.633	0.947	0.981	0.989	0.628	0.947	0.980	0.983
State FE		X	X	X		X	X	X
Time FE			X	X			X	X

Note: Robust standard errors clustered by state are reported in parentheses. Columns 4 and 8 correct for first-degree autocorrelation using Prais-Winsten estimation.

Table 3: Falsification Tests

VARIABLES	(1) Non-hybrid Honda Sales	(2) Non-hybrid Toyota Sales
Log Prius Penetration	0.068	0.079
	(0.065)	(0.094)
Log Insight Penetration	0.042	0.074
	(0.067)	(0.072)
Log Per Capita Income	0.881**	0.498
	(0.414)	(0.330)
Mean Age	4.556*	4.133
	(2.435)	(2.522)
Percent Female	1.919	5.928
	(9.721)	(9.803)
HS Grad Percent	0.434	0.421
	(0.420)	(0.370)
Percent of Adults with BA	-0.037	0.085
	(0.104)	(0.166)
LCV Score	-0.001	-0.001**
	(0.001)	(0.001)
Log Retail Gasoline Price	0.144	0.015
	(0.141)	(0.198)
Log Tax Incentives	-0.004	-0.021
	(0.017)	(0.021)
HOV lane access	0.013	-0.008
	(0.039)	(0.071)
Observations	1024	1024
R-squared	0.994	0.993

Note: Robust standard errors clustered by state are reported in parentheses. Regressions include state fixed effects and time fixed effects.

Table 4: Persistence Results

	Coefficients on Time Trend * Above Median Insight MS Q4-2001	
	(1)	(2)
	OLS	IV
t=4	-0.451**	0.0453
	(0.172)	(0.356)
t=5	-0.506***	-0.0650
	(0.168)	(0.379)
t=6	-0.506***	-0.0211
	(0.163)	(0.404)
t=7	-0.533***	-0.0482
	(0.163)	(0.401)
t=8	-0.548***	-0.105
	(0.160)	(0.386)
t=9	-0.590***	-0.161
	(0.160)	(0.389)
t=10	-0.563***	-0.172
	(0.154)	(0.369)
t=11	-0.550***	-0.187
	(0.150)	(0.349)
t=12	-0.545***	-0.252
	(0.150)	(0.351)
t=13	-0.518***	-0.237
	(0.145)	(0.332)
t=14	-0.515***	-0.237
	(0.147)	(0.338)
t=15	-0.506***	-0.202
	(0.147)	(0.329)
t=16	-0.491***	-0.203
	(0.145)	(0.328)
t=17	-0.484***	-0.209
	(0.146)	(0.327)
t=18	-0.474***	-0.216
	(0.147)	(0.327)
t=19	-0.475***	-0.220
	(0.148)	(0.333)
t=20	-0.471***	-0.239
	(0.150)	(0.333)
t=21	-0.420***	-0.256
	(0.146)	(0.316)
t=22	-0.387**	-0.265
	(0.144)	(0.304)
t=23	-0.347**	-0.261
	(0.142)	(0.296)
t=24	-0.339**	-0.275
	(0.143)	(0.298)
t=25	-0.311**	-0.262
	(0.138)	(0.297)
t=26	-0.277**	-0.251
	(0.135)	(0.299)
t=27	-0.242*	-0.225
	(0.132)	(0.297)
t=28	-0.235*	-0.232
	(0.134)	(0.298)

Note: Dependent variable is the log of cumulative hybrid vehicle sales. All specifications include time fixed effects. The t=1 through t=3 interaction terms are omitted. Standard errors are clustered by state.

Table 5: Model- and Manufacturer-Specific Effects

	Dependent Variable: Log Hybrid Vehicle Sales	
	(1)	(2)
Prius on Prius	0.502***	0.354***
	(0.0730)	(0.0777)
Prius on other Toyotas	0.214	0.209
	(0.153)	(0.209)
Prius on non-Toyotas	0.199***	0.202***
	(0.0654)	(0.0641)
Insight on Insight	-0.318**	-0.436***
	(0.128)	(0.103)
Insight on other Hondas	-0.0167	-0.00212
	(0.0569)	(0.0614)
Insight on non-Hondas	-0.0105	-0.0108
	(0.0352)	(0.0470)
Observations	4366	4366

Note: Both specifications include demographics, log retail gasoline prices, tax incentives, state-model fixed effects and model-time fixed effects, though not reported. Standard errors clustered at the state-level are reported in parentheses. Standard errors in column (2) are corrected for first-degree autocorrelation.

Table 6: Robustness Checks

	Dependent Variable: Log Hybrid Vehicle Sales				
	State-Quarter-Model Level	Linear Time Trends		Including Civic Penetration	
	(1)	(2)	(3)	(4)	(5)
Log Prius Penetration	0.318***	0.380***	0.458***	0.565***	0.580***
	(0.055)	(0.121)	(0.095)	(0.189)	(0.077)
Log Insight Penetration	-0.061**	0.001	-0.377***	-0.051	-0.496***
	(0.031)	(0.254)	(0.058)	(0.221)	(0.053)
Log Civic Penetration				-0.322	-0.007
				(0.254)	(0.017)
Log Per Capita Income	1.644***	0.172	-1.225***	0.964	0.042
	(0.434)	(0.572)	(0.351)	(0.755)	(0.408)
Mean Age	-10.835***	-26.410***	-34.926***	-11.861*	-24.606***
	(3.288)	(4.151)	(2.698)	(6.400)	(1.646)
Percent Female	-1.413	-21.472	-71.292***	47.242	-2.561
	(13.238)	(17.134)	(9.809)	(30.453)	(7.949)
High School Grad Fraction	1.187	2.441*	2.308***	1.424	0.913
	(0.839)	(1.235)	(0.553)	(1.140)	(0.615)
Percent of Adults with BA	-0.037	0.117	-0.036	0.058	0.027
	(0.203)	(0.235)	(0.138)	(0.299)	(0.157)
Average LCV Score	-0.004***	-0.003*	-0.002***	-0.003*	-0.002**
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Log Retail Gasoline Price	0.549*	0.350	0.668***	0.392	0.785***
	(0.323)	(0.404)	(0.237)	(0.467)	(0.260)
Log Tax Incentives	0.048*	0.095	0.107***	0.100*	0.102***
	(0.028)	(0.065)	(0.025)	(0.057)	(0.031)
HOV lanes access	-0.088	0.087	0.075*	0.121	0.069
	(0.064)	(0.072)	(0.042)	(0.086)	(0.043)
Observations	4,347	1,024	1,190	1,024	1,190
R-squared	0.938	0.983	0.987	0.978	0.983

Notes: The regression in column 1 includes state-model and time-model fixed effects, and standard errors are clustered at the state-quarter level and presented in parentheses. Columns 2 through 5 present IV regression results, which include state- and time-fixed effects. Standard errors are clustered at the state level. Columns 3 and 5 correct for first-degree autocorrelation.

Appendix Table 1

Instrumented Variable	Prius Penetration			Insight Penetration		
Instrument	Honda/Toyota Registration Differential	Local Honda Vehicle Assembly	Local Toyota Vehicle Assembly	Honda/Toyota Registration Differential	Local Honda Vehicle Assembly	Local Toyota Vehicle Assembly
T=4	-0.764*			-0.615***		
	(0.384)			(0.149)		
T=5	-0.774**	0.632***	0.295	-0.562***	0.146**	-0.000228
	(0.353)	(0.197)	(0.221)	(0.136)	(0.0646)	(0.0800)
T=6	-0.758**	0.128*	0.357	-0.585***	0.0332	0.0753
	(0.349)	(0.0739)	(0.216)	(0.134)	(0.0805)	(0.0704)
T=7	-0.790**	0.0283	0.405*	-0.582***	0.00498	0.0535
	(0.344)	(0.0520)	(0.209)	(0.134)	(0.0583)	(0.0654)
T=8	-0.761**	0.0555	0.437**	-0.592***	0.00309	0.0476
	(0.351)	(0.0693)	(0.204)	(0.136)	(0.0384)	(0.0635)
T=9	-0.715*	0.0481	0.484**	-0.606***	-0.0133	0.0322
	(0.362)	(0.0625)	(0.230)	(0.136)	(0.0301)	(0.0684)
T=10	-0.707*	0.0424**	0.456*	-0.604***	0.0311	0.0553
	(0.363)	(0.0175)	(0.238)	(0.138)	(0.0224)	(0.0703)
T=11	-0.704*	0.000942	0.451*	-0.593***	0.0351**	0.0484
	(0.370)	(0.0140)	(0.241)	(0.134)	(0.0150)	(0.0802)
T=12	-0.708*	-0.0164	0.438*	-0.593***	0.0223	0.0310
	(0.370)	(0.0166)	(0.237)	(0.135)	(0.0224)	(0.0760)
T=13	-0.704*	-0.0997**	0.398*	-0.588***	-0.00272	0.0250
	(0.374)	(0.0416)	(0.205)	(0.137)	(0.0242)	(0.0845)
T=14	-0.707*	-0.0940**	0.373*	-0.593***	-0.0357	0.0371
	(0.384)	(0.0463)	(0.204)	(0.138)	(0.0248)	(0.0955)
T=15	-0.711*	-0.110**	0.350*	-0.595***	-0.0277	0.0300
	(0.386)	(0.0513)	(0.206)	(0.138)	(0.0213)	(0.0945)
T=16	-0.713*	-0.107**	0.351	-0.597***	-0.0160	0.0131
	(0.386)	(0.0521)	(0.213)	(0.139)	(0.0224)	(0.0916)
T=17	-0.722*	-0.160*	0.326*	-0.606***	-0.0101	0.00376
	(0.396)	(0.0869)	(0.193)	(0.141)	(0.0343)	(0.100)
T=18	-0.722*	-0.170*	0.305	-0.609***	-0.0163	0.00922
	(0.398)	(0.0889)	(0.184)	(0.141)	(0.0374)	(0.101)
T=19	-0.720*	-0.190*	0.297*	-0.606***	-0.0146	-0.000333
	(0.403)	(0.0946)	(0.172)	(0.141)	(0.0388)	(0.0984)
T=20	-0.725*	-0.199*	0.291*	-0.609***	-0.00872	-0.000594
	(0.405)	(0.100)	(0.170)	(0.142)	(0.0370)	(0.100)
T=21	-0.709*	-0.236	0.271	-0.602***	-0.0132	0.0266
	(0.407)	(0.159)	(0.182)	(0.141)	(0.0399)	(0.0951)
T=22	-0.730*	-0.156	0.332*	-0.627***	0.0705	0.123
	(0.427)	(0.158)	(0.187)	(0.147)	(0.0481)	(0.109)
T=23	-0.720*	-0.186	0.299*	-0.651***	0.0876	0.145
	(0.427)	(0.148)	(0.178)	(0.143)	(0.0532)	(0.0971)
T=24	-0.687	-0.243	0.243	-0.643***	0.0355	0.0979
	(0.424)	(0.146)	(0.171)	(0.146)	(0.0441)	(0.0886)
T=25	-0.679	-0.243*	0.168	-0.627***	-0.00515	0.0473
	(0.424)	(0.144)	(0.160)	(0.143)	(0.0479)	(0.0891)
T=26	-0.668	-0.258*	0.146	-0.536***	-0.129*	-0.00686
	(0.422)	(0.144)	(0.161)	(0.134)	(0.0703)	(0.107)
T=27	-0.655	-0.267*	0.135	-0.521***	-0.200**	-0.0795
	(0.417)	(0.149)	(0.153)	(0.136)	(0.0962)	(0.115)
T=28	-0.648	-0.288*	0.117	-0.486***	-0.261**	-0.116
	(0.415)	(0.151)	(0.155)	(0.148)	(0.112)	(0.132)
Observations		1024			1024	
R-squared		0.985			0.965	