Within-Category Peer Effects in the Diffusion of Hybrid Electric Vehicles

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Abstract

Peer effects (also known as 'social influence and 'word-of-mouth') are believed to play a central role in the diffusion of new products and practices. Peer effects have been identified in the diffusion of new product categories, such as solar photovoltaic panels, as well as for individual products, such as the Toyota Prius hybrid-electric vehicle. In this paper we explore whether peer effects exist between distinct but related products within the same product category. We use an instrumental variables approach to identify within-category peer effects, leveraging California's high-occupancy vehicle (HOV) lane incentive for hybrid vehicle adoption for which some hybrid vehicle models were eligible and others were not. Comparing hybrid vehicle adoption in California to neighboring Oregon and Washington, we observe that the availability of the incentive resulted not only in an increase in eligible hybrid sales as expected, but also in sales of hybrid vehicle models explicitly ineligible for the incentive, which we attribute to peer effects between buyers of eligible and ineligible hybrids. We find that the sale of 1 eligible hybrid vehicle resulted in the sale of a further 0.461 ineligible hybrid vehicles, with stronger peer effects within- versus between- brands. Our results inform strategic decisions such as timing of entry and product portfolio composition, and efforts to accelerate the adoption of clean technologies and practices more broadly.

1 Introduction

Peer effects (also known as 'social influence and 'word-of-mouth') are widely believed to be an important factor in the diffusion of new behaviors, practices, and products within populations. Contacts between current and prospective adopters provide opportunities for the transfer of information that increases consumers' propensity to adopt, through mechanisms such as observational learning (Bikhchandani, Hirshleifer, & Welch, 1998), interpersonal communications (Mahajan, Muller, & Bass, 1990; Rogers, 2003) and socio-normative pressures (Van den Bulte & Lilien, 2001). Many diffusion models in the Bass tradition are founded on the assumption that social influence is a key mechanism that explains exponential growth in new product adoption. However, empirically distinguishing peer effects, in which a focal actor's actions influences decisions of others, from other effects that mimic this process is challenging (McPherson, Smith-Lovin, & Cook, 2001). Diffusion models frequently provide a good fit to empirical data without the inclusion of decision variables such as prices and consumer preferences (Bass, Krishnan, & Jain, 1994), demonstrating that factors influencing adoption are often correlated. Consistent estimation of causal peer effects therefore requires that a range of potential confounds be addressed, including homophily, the possibility that the adoption patterns observed are explained by correlated unobservables, and the potential for individuals to simultaneously be influenced while influencing others (Manski, 1993; Brock & Durlauf, 2001; Soetevent, 2006; Hartmann et al., 2008; Bollinger & Gillingham, 2012).

In this paper we contribute to the literature on peer effects by considering how peer effects operate within product categories. Existing studies of peer effects have largely concentrated on cases where the reference group comprises peers who have previously adopted the same product or category in question. For example, peer effects have been found to be influential at both the category level, for products such as solar photovoltaic panels (Bollinger & Gillingham, 2012; Graziano & Gillingham, 2014), agricultural crops (Conley & Udry, 2010), and retirement savings plans (Duflo & Saez, 2003), and at the brand level, for products such as Yahoo instant messaging (Aral, Muchnik, & Sundararajan, 2009), the Toyota Prius hybrid-electric vehicle (Narayanan & Nair, 2013), and Netgrocer.com online grocery retailing (Bell & Song, 2007; Choi, Hui, & Bell, 2010). However, these studies generally do not consider the possibility that peer effects may also operate through correlated or complementary behaviors (Aral, 2011). In the case of new products, this implies that the existence of peer effects at the category-level may be explained not just by the aggregation of within-brand peer effects for each individual brand in the category, but also by between-brand peer effects operating between products from distinct brands competing in the same product category. Clarifying how products interact within categories in the diffusion context has important implications for the strategies pursued by firms and policymakers to stimulate adoption.

We estimate the strength of peer effects between distinct but related products, within- and between- brands, in the US market for hybrid-electric vehicles (hereafter referred to as "hybrids") where products fall unambiguously within a well-defined category. We use an instrumental variables identification strategy to consistently estimate within-category peer effects, exploiting variation in California's HOV-lane incentive for hybrid-electric vehicles, relative to metropolitan regions in Oregon and Washington that did not see any similar policy change over the same period. In the first stage of our analysis we examine the effectiveness of the California hybrid HOV lane incentive, finding an increase in sales of 0.502 eligible hybrids per ZIP-code per quarter when the incentive was available. In the second stage, we find statistically significant evidence of within-category peer effects, accounting for 0.461 sales of ineligible hybrid vehicles for each eligible hybrid sold, with stronger peer effects between hybrid vehicle models of the same brand. Taken together, our results suggest that the transfer of information and social influence between consumers about the hybrid category as a whole, not just about individual hybrid makes/models, played an important role in the formation of the hybrid vehicle category and the diffusion of hybrid vehicles more broadly.

Our paper makes multiple contributions. First, while our analysis does not reveal the specific pathways by which these peer effects operate, it does allow us to conclude that within-category peer effects are an important consideration in marketing strategy decision-making. For example, exposure to a single first-mover brand may be sufficient for potential adopters to learn about the entire category, increasing the probability that they purchase other brands in the category. Second, our results build our understanding of the dynamics of market formation for new product categories, and alternative fuel vehicle (AFV) diffusion in particular. AFV diffusion is a topic of increasing concern to policy makers seeking to reduce greenhouse gas emissions and urban air pollution from transportation. Clean energy technologies are typically slow to diffuse (Menanteau & Lefebvre, 2000; Kok, McGraw, & Quigley, 2011), and our analysis highlights the importance of social influence as a driver of AFV adoption. Efforts to accelerate AFV adoption should consider how prospective adopters will get the opportunity to experience AFV technologies firsthand, and learn from the experiences of recent adopters. Further, the recognition that peer effects can operate between distinct AFV makes/models points to the potential for new market development strategies, for example introducing in multiple body styles. Finally, our methodology, while a straightforward application of instrumental variables regression, demonstrates how changes in government policy can be used to explore the influence of peer effects for products such as clean energy technologies. Our approach defines the reference group as recent adopters, in contrast with traditional installed-base models, and is appropriate for contexts where the transmission of information about adoption, for example through interpersonal communications, is thought to be influential.

The remainder of the paper is organized as follows. In §2 we discuss challenges in the consistent estimation of causal peer effects, and lay out our instrumental variables identification strategy. In §3, we describe our empirical setting and data, providing background on the California market for hybrid vehicles and the high-occupancy vehicle (HOV) incentive that we use as our instrument. In §4, we present our results, estimating the strength of within-category peer effects and exploring variation in the strength of peer effects within- and between- brands. §5 concludes with a discussion of the managerial implications of our findings.

2 Identification Strategy

2.1 Challenges in the Identification of Peer Effects

While social influence plays a central role in many marketing theories, empirical estimation of social influence mechanisms has been a persistent challenge. Patterns consistent with theories about social influence such as the clustered patterns of adoption are frequently observed. However, establishing that a casual social influence mechanism exists requires that three potential confounds be addressed. First, these patterns may result from endogenous group formation, because of the tendency for like-minded people to congregate together. For example, hybrid vehicle adoption may be expected to be higher in suburbs where more affluent and left-leaning residents congregate who hold stronger preferences for environmental sustainability (DellaPosta, Shi, & Macy, 2015). Second, adoption patterns may be influenced by correlated unobservables. For example, hybrid vehicle adoption may be influenced by changing societal attitudes towards climate change over time, which may or may not be consistent across the population. Third, the potential for simultaneity in social influence can be problematic if agents are influencing others in their reference group while also being influenced by that group. These challenges have been well documented in the peer effects literature (including (Manski, 1993; Brock & Durlauf, 2001; Soetevent, 2006; Hartmann et al., 2008; Bollinger & Gillingham, 2012)) and we do not elaborate on them here, except to emphasize the central role that these empirical challenges play in studies of peer effects. Narayanan & Nair (2013) state succinctly that *"It is now taken as fait accompli in the empirical literature that the credibility of measures of social influence rests on the extent to which these confounds are appropriately addressed."*

A range of empirical strategies have been used in the peer effects literature to address these identification challenges. Rich specification of fixed effects, including fixed effects by peer group, time, and potentially peer group-time, can control for the potential influence of self-selection and correlated unobservables (Hartmann et al., 2008). A consequence of this approach is that the inclusion of these fixed effects quickly makes the estimation of non-linear models infeasible for large datasets, necessitating the use of linear models (Narayanan & Nair, 2013). To address the problem of simultaneity, a strategy commonly used is to make use of an exclusion restriction, in which an instrumental variable is introduced that influences the decision of a focal agent but which by definition cannot plausibly influence the decisions of that agent's reference group (Nair, Manchanda, & Bhatia, 2006; Hartmann et al., 2008). While this instrumental variables approach is attractive and straightforward to implement, it relies on finding suitable instruments, which can be challenging in practice (Bollinger & Gillingham, 2012).

2.2 Our Approach

Our identification strategy uses instrumental variables to consistently estimate the strength of peer effects between different hybrid vehicle makes and models in California, the largest market for hybrid vehicles in the United States. We exploit variation resulting from the design of California's High Occupancy Vehicle (HOV) lane access incentive for hybrid vehicle adoption offered in the mid-2000s, which allowed buyers of eligible hybrid vehicles single-occupant use of HOV lanes usually restricted to vehicles with 2 or 3 occupants. Crucially for our purposes, the incentive was only available to buyers of hybrid vehicle models that achieved an EPA highway fuel economy rating of 45 miles per gallon (mpg) or more, providing our exclusion restriction. Only 3 of the 13 hybrid vehicle models available in the United States at that time were eligible for the incentive, meaning that any increase in sales of the 10 ineligible hybrid models cannot be attributed to the incentive directly. If within-category peer effects were influential in this market, we would expect that the effect of the incentive would result not only in an increase in sales of eligible hybrid vehicle models as intended, but also to an increase in sales of hybrid models explicitly ineligible for the incentive, due to interactions between buyers of eligible and ineligible hybrids in those regions.

We define the reference group both temporally and geographically, considering only recent adopters who have purchased an eligible hybrid model in the same region in the current time period. Generally, social influence tends to be stronger from recent adopters of new technologies than from previous adopters captured in the installed base (Risselada, Verboef, & Bijmolt, 2014). Our conceptualization is consistent with peer effects mechanisms such as interpersonal communications, in contrast with installed base models, which are more consistent with mechanisms such as observational learning. We propose that the experiences of recent adopters are likely to be persuasive for prospective adopters in this context, because hybrid vehicles are expensive and challenge long-held social norms about how vehicles operate (e.g. near-silent operation and regenerative braking). Such complex technologies have a significant adoption threshold, and typically require direct interactions among peers prior to adoption (Centola & Macy, 2007). Our approach also has practical advantages. It is generally easier to find appropriate instruments for the rate of adoption (e.g. government policy changes), rather than the installed base of adopters, which is a stock variable that accumulates consumers' adoption decisions (Bollinger & Gillingham, 2012).

We specify a linear panel model to estimate the strength of peer effects between eligible and ineligible hybrid vehicle models, where the dependent variable is the ZIP code z-quarter q rate of sales of hybrid vehicle models that are *ineligible* for the California HOV lane incentive $s_{zq}^{ineligible}$. The peer effect of interest is the influence of $s_{zq}^{eligible}$, the ZIP code z-quarter q sales of hybrid vehicle models that are *eligible* for the California hybrid HOV lane incentive. We therefore seek to estimate the following model:

$$s_{zq}^{ineligible} = \beta s_{zq}^{eligible} + f_z + f_q + \gamma K_{zq} + \varepsilon_{zq} \tag{1}$$

where $f_{z,}$ is the ZIP code-specific fixed effect, f_q is the quarter fixed effect, K_{zq} is a set of demographic and market controls, and ε_{zq} is the residual. The coefficient β is the peer effect to be estimated.

If $s_{zq}^{eligible}$ is correlated with the residual, then Ordinary Least Squares (OLS) estimation will lead to biased estimates of β. We therefore supplement traditional fixed effects OLS estimation of Eq. 1 with two-stage least squares (2SLS) instrumental variables estimation. In the 2SLS approach, we first estimate the effect of the California hybrid HOV lane incentive (by county) on consumer adoption of eligible hybrid vehicles in each ZIP code z:

$$s_{zq}^{eligible} = \delta HOV_{cq} + f_{1z} + f_{1q} + \gamma K_{1zq} + \varepsilon_{1zq} \tag{2}$$

where: HOV_{cq} is a dummy variable taking the value 1 if the HOV lane incentive is available in quarter q and an HOV lane exists in the county c in which ZIP code z resides (0 otherwise), and δ is a parameter measuring the effect of the HOV lane incentive on sales of eligible models in each ZIP code. In the 2nd stage, we then estimate the effect of the fitted values of eligible sales on sales of each ineligible hybrid vehicle model in the same ZIP code:

$$s_{zq}^{ineligible} = \beta \hat{s}_{zq}^{eligible} + f_{2z} + f_{2q} + \gamma K_{2zq} + \varepsilon_{2zq} \tag{3}$$

where $\hat{s}_{zq}^{eligible}$ is the predicted values of eligible hybrid sales in ZIP code z in quarter q from the 1st stage.

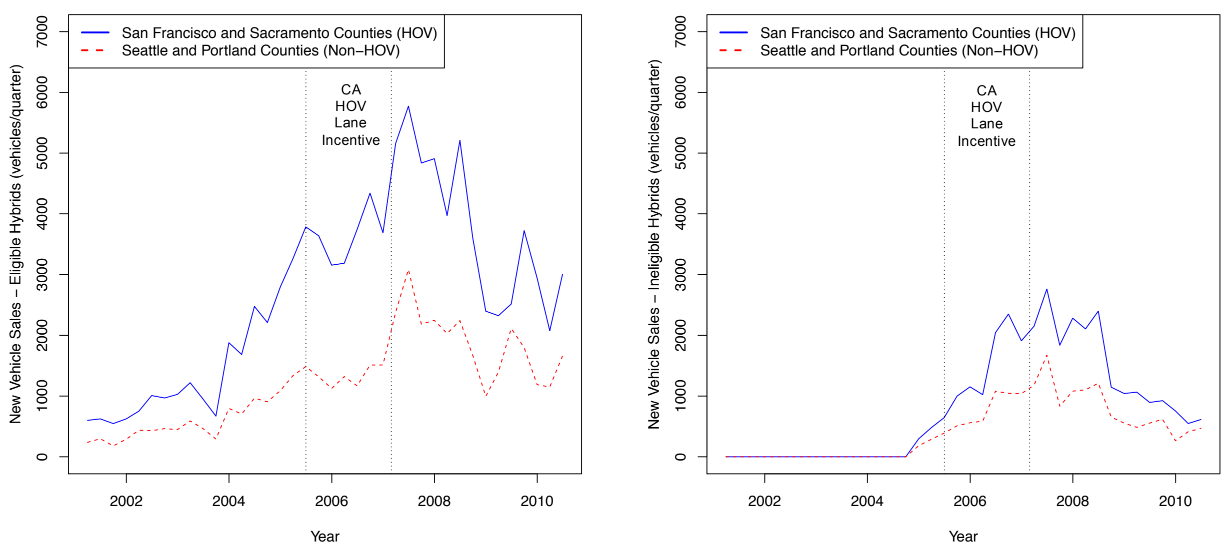
3 Empirical Setting

Hybrid vehicles that combine a conventional gasoline engine with an electric motor to reduce fuel consumption and tailpipe emissions were first introduced in the United States in late 1999. The US hybrid vehicle market grew steadily during the 2000s as growing number of hybrid vehicle makes and models entered the market, supported by significant government incentives to encourage hybrid vehicle adoption. We compile a ZIP-code level spatiotemporal dataset to explore whether peer effects contributed to the growth of hybrid vehicle sales during this time. We obtained data on spatiotemporal new vehicle registrations in the United States from R.L. Polk & Co. (now IHS Automotive), an automotive industry data provider. Our dataset contains quarterly sales of each hybrid vehicle model in each US ZIP code from January 2001 to June 2010 inclusive (q = 38). We supplement this with ZIP-code level demographic data from the American Community Survey via Social Explorer, and time-series data on gas prices from the U.S. Energy Information Administration.

Although hybrid vehicles have now been available in the US for nearly two decades, consumer adoption has been slow, with the hybrid vehicle category accounting for no more than 3% of new vehicle sales (HybridCars.com, 2016). Hybrid vehicles have received generous policy support at various times to incentivize consumer adoption, including a Federal income tax credit in the mid-2000s worth up to $3,150, and various state government policies such as income tax credits, sales tax exemptions, and single-occupant access to HOV lanes (e.g. the Californian policy that we study in this paper).

For the purpose of estimating peer effects, we concentrate our attention on San Francisco and Sacramento in Northern California (San Francisco-Sacramento), a region of high hybrid vehicle adoption (defined formally as the 9 counties in the Bay Area, plus the 4 counties in the Sacramento-Roseville-Arden Arcade Metropolitan Statistical Area (MSA)). Consumers living in the San Francisco-Sacramento region were eligible to receive the California HOV-lane incentive upon purchasing a qualifying hybrid vehicle (which we detail below), and geographic proximity to HOV lanes that made this incentive valuable. The most natural control group for this analysis is the metropolitan regions of Seattle and

Portland (Seattle-Portland) in the neighboring states of Washington and Oregon on the West Coast (defined formally as the 7 counties in the Seattle-Tacoma-Bellevue WA MSA plus the 7 counties in the Portland-Vancouver-Hillsboro OR-WA MSA). Consumers in the Seattle-Portland region were legally not eligible to receive the California incentive, and were not exposed to other equivalent policy shocks, but were otherwise very similar. Figure 1 shows that sales of hybrid vehicles in the San Francisco-Sacramento and Seattle-Portland regions are very highly correlated (r = 0.93 for eligible hybrids and r = 0.99 for ineligible hybrids). Hybrid sales grew steady through the mid-2000s, before plateauing and declining from 2008 when the US automotive market contracted significantly during the financial crisis (FRED, 2017).

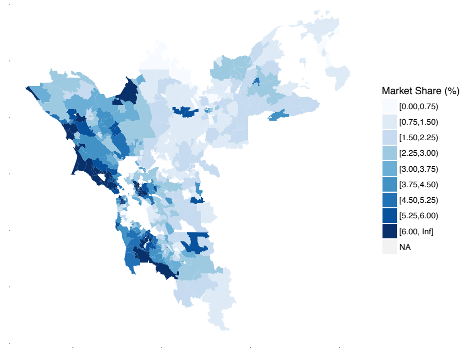


(a) Quarterly Sales – Eligible Hybrids

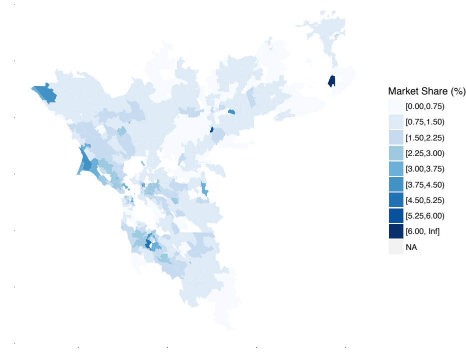
(b) Quarterly Sales – Ineligible Hybrids

Figure 1: Hybrid Vehicle Sales – January 2001 to June 2010

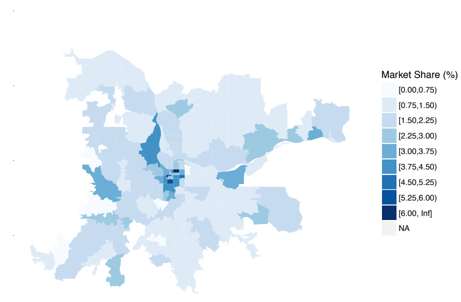
Figure 2 shows the cumulative market shares of eligible (left) and ineligible (right) hybrid vehicles by ZIP code in both regions for the period January 2001 to June 2010 inclusive (cumulative hybrid sales / cumulative light vehicle sales). Clustered patterns of hybrid vehicle adoption are observed, with a noticeable correlation between eligible and ineligible hybrids in each region, patterns consistent with causal within-category peer effects. Finally, we compare demographics for the two regions in Table 1. Compared to the United States as a whole, these regions both have relatively higher household incomes, higher levels of education, similar levels of car dependence, and Democrat-leaning political preferences, which we use as a proxy for environmental preferences.



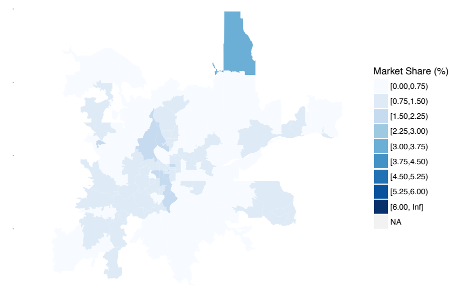
(a) Cumulative Market Share – Eligible Hybrids San Francisco and Sacramento CA



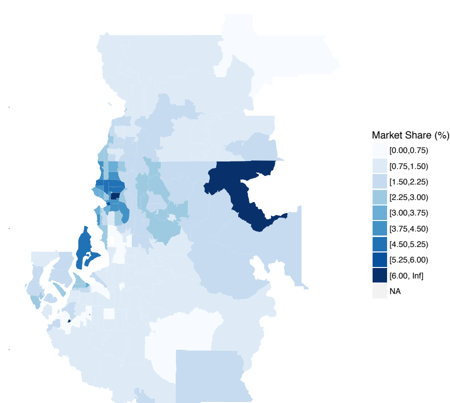
(b) Cumulative Market Share – Ineligible Hybrids San Francisco and Sacramento CA



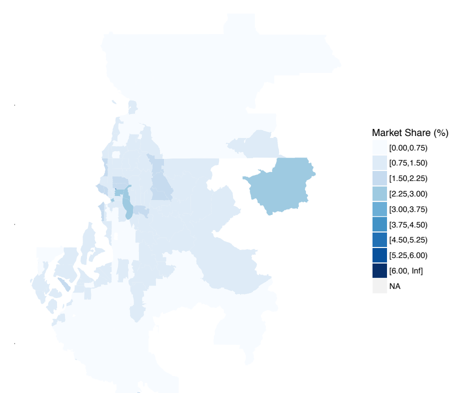
(c) Cumulative Market Share – Eligible Hybrids Portland-Vancouver-Hillsboro OR-WA



(d) Cumulative Market Share – Ineligible Hybrids Portland-Vancouver-Hillsboro OR-WA



(e) Cumulative Market Share – Eligible Hybrids Seattle-Tacoma-Bellevue WA



(f) Cumulative Market Share – Ineligible Hybrids Seattle-Tacoma-Bellevue WA

<u>Figure 2: Hybrid Vehicle Market Share by ZIP Code – January 2001 to June 2010</u>

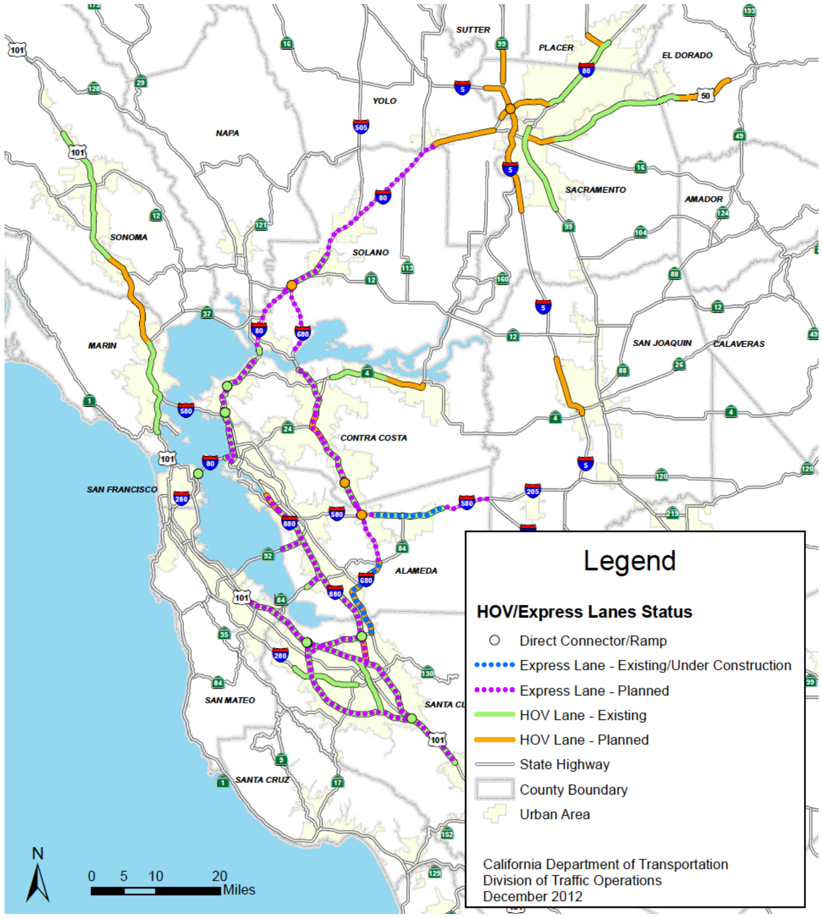
Table 1: Demographic Summary Statistics

	San Francisco & Sacramento		Seattle & Portland		United States	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Population (total)	9,205,165		6,221,753		309,582,594	
Political Preference (% Democrat in 2008 Pres. Election)	69.3%	9.8%	62.8%	8.4%	53.4%	14.5%
Average Household Size (# of people)	2.76	0.47	2.53	0.32	2.66	0.43
Median Household Income ($/year)	77,280	26,304	65,367	18,487	56,394	23,118
% Population Male	49.5%	2.6%	49.7%	2.2%	49.1%	2.9%
% Population White	58.8%	19.4%	77.8%	12.2%	74.1%	22.2%
% Population Bachelor degree or greater	38.6%	18.1%	34.7%	16.8%	27.8%	16.1%
% Population Aged 18-44	38.5%	8.3%	38.8%	7.7%	36.8%	7.9%
% Population Aged 65+	12.1%	4.4%	11.2%	3.5%	12.9%	5.5%
% Population Drive to Work Alone	69.6%	13.2%	71.3%	9.9%	76.1%	13.4%
% Population 30 Min+ Commute to Work	38.1%	9.9%	37.2%	10.2%	34.1%	14.6%
% Dwellings Owner-Occupied	59.4%	16.4%	63.9%	15.4%	66.3%	17.3%
Median Dwelling Value ($)	541,887	232,269	334,618	115,874	235,831	169,291

Data Source: ACS (2011)

3.1 California's Hybrid High Occupancy Vehicle (HOV) Lane Incentive

Our identification strategy exploits variation in the state of California's incentive for hybrid vehicle adoption in the mid-2000s that allowed single-occupant use of hybrid vehicles in high occupancy vehicle (HOV) lanes. HOV lanes are traffic lanes reserved for the exclusive use of vehicles containing the driver and at least one passenger. The construction of HOV lanes began in California in the 1970s with the objective of both relieving traffic congestion on California highways, and encouraging vehicle sharing to conserve fuel and lessen air pollution (Caltrans, 2017). In Northern California, HOV lanes exist through the San Francisco Bay Area, and around Sacramento, the capital of California (Figure 3). These HOV lanes operate on a part-time basis, functioning as HOV lanes at peak hours (6-10am and 3-7pm) Monday to Friday, and regular lanes at other times.



<u>Figure 3: High Occupancy Vehicle (HOV) Lanes in the Northern California Region (Caltrans, 2012)</u>

The California HOV lane incentive for hybrid vehicles was introduced in August 2005, allowing buyers of eligible hybrid vehicles single-occupant use of the existing HOV lane network in California. To qualify, the buyer had to purchase a hybrid vehicle that achieved an EPA-rated highway fuel economy of 45 miles per gallon (mpg) or above, as defined in California statute AB 2628. Qualifying hybrid purchases were issued with yellow Clean Air Vehicle decals that clearly identified the vehicle as being eligible for single-occupant HOV use. While 13 hybrid vehicle models were on sale in California during this time, only three of these models achieved the required 45 mpg or above: The Toyota Prius, the Honda Civic Hybrid and the Honda Insight. We hereafter refer to those hybrid vehicle models eligible for the HOV lane incentive as 'eligible', and all other hybrid models as 'ineligible'. The incentive ended in

February 2007 when the cap of 85,000 Clean Air decals was reached (CARB, 2011). These decals were valid until June 2011, after which time single-occupant use of hybrids in HOV lanes was no longer allowed.

Evidence from prior studies on the effect of the California hybrid HOV lane incentive on hybrid vehicle sales is mixed. Analyzing used car prices, Shewmake & Jarvis (2014) find the hybrid HOV Clear Air decals to be valuable, estimating consumer willingness-to-pay at $1,000-$2,000 per year. However, Gallagher & Muehlegger (2011) analyze quarterly state-level sales data from 2000-2006 and do not find a significant effect of California's HOV lane incentive on per-capita hybrid sales.

3.2 Eligible and Ineligible Hybrid Makes/Models

Finally, we provide details of the individual makes (brands) and models of hybrid vehicle available in the United States during the period that we study. Table 2 shows the attributes of each hybrid make/model, including EPA highway fuel economy, the criteria for eligibility for the California HOV lane incentive. Table 3 shows sales of each make/model pre-, during-, and post- the availability of the HOV lane incentive. These data reveal several interesting observations. First, the iconic Toyota Prius is clearly dominant, accounting for 56% of all hybrid sales, and 80% of eligible hybrid sales. This is noteworthy because the Prius was readily observable as a hybrid due to its distinctive aerodynamic design, and because it was the only one of these models (other than the niche Honda Insight) that was a dedicated hybrid model. All the other makes/models, in contrast, were available in both conventional gasoline and hybrid variants, with the hybrid variant only distinguishable by subtle changes such as different badges on the trunk lid. Second, the HOV-eligible hybrid makes/models were compact cars and hatchbacks, while the less efficient HOV-ineligible hybrids are larger sedans and SUVs. The HOV-eligible and HOV-ineligible hybrids therefore exist in different market segments, likely to result in less cross-shopping on the basis of vehicle body style. These artefacts may contribute to our understanding of the origins of peer effects within the hybrid category to the extent they are influential. Third, several hybrid makes/models were only introduced after the HOV incentive commenced.

Table 2: Hybrid Vehicle Characteristics by Make/Model

	Make	Model	EPA Size Class	Market Launch Date	’06/’07 Fuel Economy (mpg highway)
HOV Eligible	Honda	Civic	Car - Compact	Q1 2002	45
	Honda	Insight	Car – Two Seater	Q4 1999	49
	Toyota	Prius	Car - Midsize	Q2 2000	45
HOV Ineligible	Ford	Escape	Light Truck - SUV	Q4 2004	28
	Honda	Accord	Car - Midsize	Q4 2004	31
	Lexus	GS	Car - Midsize	Q2 2006	25
	Lexus	RX	Light Truck - SUV	Q2 2005	25
	Mercury	Mariner	Light Truck - SUV	Q4 2005	26
	Nissan	Altima	Car - Midsize	Q1 2007	33
	Saturn	Aura	Car - Midsize	Q1 2007	32
	Saturn	Vue	Light Truck - SUV	Q3 2006	29
	Toyota	Camry	Car - Midsize	Q2 2006	34
	Toyota	Highlander	Light Truck - SUV	Q2 2006	27

Table 3: Hybrid Vehicle Sales by Make/Model

			San Francisco and Sacramento				Portland and Seattle			
	Make	Model	Sales Pre-Incentive	Sales During Incentive	Sales Post-Incentive	% of Hybrid Sales	Sales Pre-Incentive	Sales During Incentive	Sales Post-Incentive	% of Hybrid Sales
HOV Eligible	Honda	Civic	6,957	5,012	6,254	12%	3,112	2,015	3,136	12%
	Honda	Insight	710	81	1680	2%	363	58	905	2%
	Toyota	Prius	20,128	21,899	41,028	56%	8,297	8,319	20,620	56%
HOV Ineligible	Ford	Escape	707	2638	4995	6%	498	1548	2519	7%
	Honda	Accord	587	1007	173	1%	289	527	93	1%
	Lexus	GS	0	176	190	0%	0	58	42	0%
	Lexus	RX	363	2796	3617	5%	166	1078	1727	4%
	Mercury	Mariner	0	148	229	0%	0	160	244	1%
	Nissan	Altima	0	91	5401	4%	0	1	424	1%
	Saturn	Aura	0	1	63	0%	0	0	42	0%
	Saturn	Vue	0	210	412	0%	0	130	318	1%
	Toyota	Camry	0	3419	8588	8%	0	1432	4236	8%
	Toyota	Highlander	128	4032	3786	5%	74	2145	2457	7%
	Total Sales		29,580	41,510	76,416		12,799	17,471	36,763	
	% of Total Sales		20%	28%	52%		19%	26%	55%	

We exclude three hybrid vehicle models from the empirical analysis that follows where insufficient sales exist during the period of the California HOV lane incentive to consistently estimate peer effects. First, we exclude the HOV-eligible Honda Insight, because the 1st generation two-door Insight was removed from the market in 2006, and was not available until the larger 2[nd] generation Insight was introduced in 2009. Second, we exclude the HOV-ineligible Saturn Aura hybrid, because it had too few sales. Third, we exclude the Nissan Altima hybrid, because this model was only introduced in the 4th quarter of 2006, providing only two observations per ZIP code during the period that the incentive was available.

4 Results

We now present the results of our empirical analysis. The following results are estimated using data from the 4th quarter of 2004, when the first HOV-ineligible hybrids entered the market to the 2th quarter of 2010 (inclusive), the end of our dataset. In addition to ZIP- and quarter- fixed effects, we include a range of controls. First, we include quarterly light vehicle sales by ZIP code to control for changes in the size of the vehicle market over time. Second, we include a number of interaction variables (income * gas price, education * gas price, average commuting time * gas price, and Democrat voting percentage * gas price) to control for consumers' potentially differing responses to changing gas prices. Third, we include dummy variables for other policy changes that occurred towards the end of the period we study: the introduction of a hybrid vehicle sales tax exemption in Washington state in January 2009, and the ending of a hybrid vehicle income tax credit in Oregon in December 2009 that had been available since before the start of the period we study.

We begin by estimating the effectiveness of the California HOV lane incentive, and the resulting aggregate peer effect of eligible hybrid sales on ineligible hybrid sales. We then make various elaborations to enhance our understanding of how these peer effects operate.

4.1 The Effectiveness of the California HOV Lane Incentive

We estimate the strength of within-category peer effects in two stages. In the first stage of our analysis, we consider the effect of our instrument, the California HOV lane incentive, on sales of eligible hybrid vehicles (Table 4).

Table 4: Effectiveness of the California HOV Lane Incentive

	1st Stage (1)	**1st Stage (2)**
Hybrid HOV Incentive	0.234**	0.502***
	(0.108)	(0.114)
Fixed Effects	All	Selected
R^2	0.0003	0.001
F-statistic	4.687**	19.267***

Significance levels: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Our results indicate that the California HOV lane incentive had a positive and statistically significant effect on hybrid vehicle adoption. Estimating the 1st stage with all fixed effects, we find that the HOV lane incentive resulted in an additional 0.234 eligible hybrid vehicle sales per ZIP code per quarter in San Francisco and Sacramento during the period that the incentive was available. Given the high number of controls relative to the number of data points, we also estimate the model using the 'post-double-selection' method (Belloni, Chernozhukov, & Hansen, 2013), which selects out the controls that are predictive of neither the dependent or independent variables of interest. We use Lasso to perform variable selection using the theoretically motivated penalty level (Belloni, Chen, Chernozhukov, & Hansen, 2012). Doing so, we obtain an estimate of 0.502 eligible hybrid sales per ZIP code per quarter. Using this approach, we obtain an F-statistic of 19.267 that satisfies the multiple threshold criteria for strong instruments proposed by Stock & Yogo (2005), meaning that we can use the HOV lane incentive as a valid instrument for the purpose of identifying within-category peer effects in Northern California.

Aggregating the effect of the incentive across the San Francisco and Sacramento region, we can attribute 2,059 sales of eligible hybrid vehicles in Northern California to the availability of the HOV lane incentive, representing 8% of the 26,922 eligible hybrid vehicles sold in San Francisco and Sacramento during this time. Our analysis using spatiotemporal data therefore suggests that single-occupant HOV lane incentives can be effective at accelerating alternative fuel vehicle (AFV) adoption, consistent with (Shewmake & Jarvis, 2014), and in contrast with some earlier studies (e.g. Gallagher & Muehlegger (2011)).

4.2 The Peer Effect of Eligible Hybrid Sales on Ineligible Hybrid Sales

In the second stage of our analysis, we estimate the strength of peer effect of eligible hybrid sales on ineligible hybrid sales, using both OLS (Eq. 1) and 2SLS (Eqs. 2 and 3). These results are shown in Table 5:

Table 5: Peer Effect of Eligible Hybrid Sales on Ineligible Hybrid Sales

	OLS (1)	**OLS (2)**	**2SLS (3)**	**2SLS (4)**
Peer Effect – Eligible Sales (β)	0.165***	0.170***	0.874**	0.461***
	(0.004)	(0.004)	(0.422)	(0.147)
Fixed Effects	All	Selected	All	Selected

Significance levels: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

In the OLS model with lasso-selected fixed effects, the sale of each one eligible hybrid is found to result the sale of a further 0.170 ineligible hybrids, a result that is statistically significant. In the comparable 2SLS model, where the IV estimator is asymptotically unbiased, the sale of each one eligible hybrid leads to the sale of a further 0.461 ineligible hybrids, which is both statistically significant, and significantly larger than the OLS estimate. Application of the Wu-Hausman test confirms that peer effects in hybrid vehicle diffusion are endogenous (rejecting the null hypothesis of exogeneity with $p < 0.05$). We therefore conclude that within-category peer effects played an important role in the diffusion of hybrid vehicles during this time. Our approach does not allow us to isolate the specific pathway through which this influence occurs. However, we may speculate that mechanisms such as interpersonal communications are important, because these peer effects originate from a reference group who has recently adopted hybrid vehicles themselves.

Using these results, we can calculate the number of additional ineligible hybrid sales that can be attributed to the HOV lane incentive through the mechanism of peer effects. As a result of the 2,059 additional sales of eligible hybrid vehicles, a further 949 sales of ineligible hybrid vehicles can be attributed to the HOV lane incentive, representing 7% of the 14,518 ineligible hybrids sold in Northern California during the period of the incentive. These results demonstrate that the effectiveness of policies intended to incentivize adoption of clean technologies, such as the HOV lane incentive we study here, may be greater than previously believed.

4.3 Exploring Heterogeneity in Peer Effects

It is likely that heterogeneity exists in the peer effect estimates shown in Table 5, because the attraction of hybrid vehicles transcends the fuel economy benefits for many buyers, also providing status value regarding the owner's environmental credentials. Some consumers are highly likely to adopt hybrids, including ineligible makes/models, irrespective of whether they are exposed to eligible hybrids. Others will not even consider purchasing a hybrid of any type, and exposure to eligible hybrids won't change their decision. In the presence of such heterogeneity, differences in OLS and 2SLS estimates are to be expected, because OLS estimation capture the average peer effect across all ZIP codes, while 2SLS estimation captures the local average treatment effect in those ZIP codes marginal in the eligible hybrid adoption decision.

To test for heterogeneity in peer effects, we stratify our sample in multiple ways. First, consumers with long commutes may reasonably be expected to respond differently than consumers with short commutes upon being exposed to hybrid vehicles, given different fuel expenditures and vehicle requirements. To test this we divide our sample of treated California ZIP codes into two groups, those with average commuting times (in minutes) above and below the median of the full sample, and estimate our peer effects models for each group (Table 6). Here we observe significant differences between groups. In the 1st stage, the response to the HOV lane incentive is positive and statistically significant in both groups, although larger for the group with shorter average commuting times. Estimating the full models, we find OLS estimates of peer effects that are also positive and statistically significant for both groups, again larger for the shorter commute group. Our 2SLS peer effect estimates, in contrast, exhibit distinct heterogeneity between groups. For the shorter commute group our 2SLS peer effect estimate is large and highly statistically significant (0.792^{***}), while our estimate for the longer commute group is not statistically significant. That is, while consumers with shorter commutes and consumers with longer commutes were both influenced by the HOV lane incentive, it was primarily consumers with shorter commutes who were influenced by hybrid vehicle peer effects. This result may be somewhat surprising, because it is the longer commuting group that would be expected to have greater opportunity for observational learning about hybrids given more time spent on the road, and potentially greater incentive to invest in fuel economy if longer commute times are correlated with higher vehicle miles travelled. One possible explanation is that peer effects are influential in the shorter commuting group because these ZIP codes are generally in denser and more urban areas where the status signaling benefits of hybrid vehicle ownership may be more salient.

Table 6: Peer Effect Heterogeneity by Commuting Time Strata

	1st Stage (1)	**1st Stage (2)**	**OLS (3)**	**OLS (4)**	**2SLS (5)**	**2SLS (6)**
Hybrid HOV Incentive * Short Commute	0.792*** (0.197)	-	-	-	-	-
Hybrid HOV Incentive * Long Commute	-	0.132 (0.154)	-	-	-	-
Peer Effect * Short Commute	-	-	0.179*** (0.005)	-	0.610*** (0.171)	-
Peer Effect * Long Commute	-	-	-	0.158*** (0.008)	-	0.610 (0.869)
Fixed Effects	Selected	Selected	Selected	Selected	Selected	Selected

Significance levels: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

To further explore the demographic determinants of peer effect heterogeneity, we also estimate models where we stratify our sample of California ZIP codes by income (Table 7) and by education (Table 8). We find that the HOV lane incentive only had a statistically significant impact in ZIP codes with relatively lower incomes, with statistically significant 2SLS peer effects found in those same ZIP codes. It might reasonably be expected that consumers with relatively lower incomes are more responsive to the government incentive, given less discretionary income to spend on an expensive hybrid vehicle. However, it is interesting that peer effects are still influential within this group, leading to higher adoption of HOV-ineligible hybrids. With respect to education, the HOV lane incentive only had a statistically significant impact in ZIP codes with higher fractions of the population having a Bachelor's degree or greater, also leading to statistically significant peer effects in these same high education ZIP codes. These results provide clear evidence of heterogeneity in peer effects, confirming that our 2SLS estimates are capturing peer effects specifically for the ZIP codes marginal in the eligible hybrid adoption decision. It is therefore not surprising that our 2SLS estimates are larger than our OLS estimates, since the effect of eligible hybrid sales on ineligible hybrid sales is also likely to be greater in ZIP codes that are marginal in the eligible hybrid adoption decision.

Table 7: Peer Effect Heterogeneity by Income Strata

	1st Stage (1)	**1st Stage (2)**	**OLS (1)**	**OLS (2)**	**2SLS (3)**	**2SLS (4)**
Hybrid HOV Incentive * Low Income	0.709^{***} (0.127)	-	-	-	-	-
Hybrid HOV Incentive * High Income	-	0.175 (0.233)	-	-	-	-
Peer Effect * Low Income	-	-	0.138^{***} (0.005)	-	0.250^{**} (0.102)	-
Peer Effect * High Income	-	-	-	0.180^{***} (0.008)	-	1.291 (1.659)
Fixed Effects	Selected	Selected	Selected	Selected	Selected	Selected

Significance levels: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table 8: Peer Effect Heterogeneity by Education Strata

	1st Stage (1)	**1st Stage (2)**	**OLS (1)**	**OLS (2)**	**2SLS (3)**	**2SLS (4)**
Hybrid HOV Incentive * Low Education	0.265 (0.177)	-	-	-	-	-
Hybrid HOV Incentive * High Education	-	0.749^{***} (0.145)	-	-	-	-
Peer Effect * Low Education	-	-	0.192^{***} (0.005)	-	1.051 (0.662)	-
Peer Effect * High Education	-	-	-	0.142^{***} (0.007)	-	0.349^{***} (0.134)
Fixed Effects	Selected	Selected	Selected	Selected	Selected	Selected

Significance levels: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

4.4 Are Within-Category Peer Effects Conditioned by Vehicle Brand?

If marketing practitioners are to effectively leverage these peer effects during new product launch, it is necessary to understand how these peer effects operate differently within- and between- brands. We next estimate the strength of peer effects from eligible hybrid vehicles to each individual ineligible hybrid make/model, using both OLS and 2SLS. Table 9 summarizes our peer effect estimations for each ineligible hybrid make/model, using various estimation approaches.

Table 9: Summary of Make/Model Peer Effects

Make Model	**Ford Escape**	**Honda Accord**	**Lexus GS**	**Lexus RX**	**Mercury Mariner**	**Saturn Vue**	**Toyota Camry**	**Toyota Highlander**
OLS	0.019^{***}	0.0002	0.002^{***}	0.008^{***}	0.002^{***}	-0.002^{**}	0.126^{***}	0.014^{***}
(All Fixed Effects)	(0.002)	(0.001)	(0.0003)	(0.001)	(0.0004)	(0.001)	(0.004)	(0.002)
OLS	0.026^{***}	0.001^{*}	0.002^{***}	0.006^{***}	0.002^{***}	-0.002^{**}	0.127^{***}	0.021^{***}
(Selected Fixed Effects)	(0.002)	(0.001)	(0.0003)	(0.001)	(0.0004)	(0.001)	(0.003)	(0.002)
2SLS	-0.164	0.052	0.029	0.326	-0.006	0.033	0.147	0.272^{*}
(All Fixed Effects)	(0.157)	(0.046)	(0.020)	(0.229)	(0.030)	(0.048)	(0.181)	(0.146)
2SLS	0.009	0.050^{**}	0.033^{***}	0.120^{***}	-0.006	0.040^{**}	0.219^{***}	0.096^{***}
(Selected Fixed Effects)	(0.065)	(0.021)	(0.010)	(0.051)	(0.015)	(0.016)	(0.072)	(0.030)

Significance levels: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Here we observe significant variation in the strength of peer effects across different makes/models of ineligible hybrid vehicle. Focusing on the consistently estimated 2SLS parameters with lasso-fixed effects, we observe considerable variation in the statistical significance and magnitude of make/model-level peer effect estimates. Our peer effect estimates are large and statistically significant for the Toyota Camry (0.219), Toyota Highlander (0.096) and Lexus RX (0.12). In contrast, our estimates are positive and statistically significant but modest (in the range 0.033 – 0.050) for the Honda Accord, Lexus GS, and Saturn Vue, and not statistically significant for the Ford Escape and Mercury Mariner. To the extent that the origins of these peer effects can be attributed primarily to the dominant and distinctive Toyota Prius, these results suggest that brand is an important moderator of the strength of within-category peer effects, with ineligible Toyota hybrid models benefiting from substantially stronger peer effects compared to non-Toyota hybrids.

These within-category interactions have important strategic implications for managers launching new products in competitive emerging markets. Positive between-brand peer effects provide later entrants an opportunity to benefit from the success of the first mover, allowing a shorter takeoff time for those later entrants and faster diffusion of the category as a whole (2^{nd} mover advantage). However, stronger within-brand peer effects may provide a reinforcing advantage to the first mover, leveraging peer effects from early adopters to launch new products and acquire yet more customers (1^{st} mover advantage). Taken together, these mechanisms generate complex dynamics of category, brand, and product growth. One such patterns is the "dual pattern of growth", proposed by Libai, Muller, & Peres (2009), characterized by a fast takeoff for the second entrant, but a strengthening advantage over time for the market pioneer, all else being equal. The strength of this advantage depends on the relative magnitudes of the within-brand versus between-brand peer effects, which we find to be quite substantial in the hybrid vehicle market. Consistent with this theory, Toyota's early entry into the hybrid market has resulted into lasting market dominance even with increasing competition. As of August 2017, Toyota held 46% market share within the hybrid vehicle category, despite only manufacturing 7 of the 45 hybrid vehicle models currently available in the United States.

4.5 Demographic Determinants of Adoption

Another question of interest to marketers is where they should target their marketing efforts geographically to leverage peer effects most successfully. Regions that have a higher propensity to adopt should have a lower cost of customer acquisition, resulting in more effective marketing campaigns and faster diffusion. To understand the underlying determinants of hybrid vehicle adoption, we next add demographic controls to the model. In Table 10, we estimate the OLS model (Eq. 1), removing the ZIP-code fixed effects and replacing them with a variety of ZIP-code demographic controls from the American Community Survey 2007-2011 5-year averages (ACS, 2011).

Table 10: Demographics Model

	OLS
Peer Effect – Eligible Sales (β)	0.294*** (0.004)
Political Preference (% Democrat in 2008 Pres. Election)	0.432*** (0.124)
Average Household Size	-0.429*** (0.101)
Median Household Income	2.426*** (0.274)
% Population Male	0.389 (0.716)
% Population White	-1.475*** (0.223)
% Population Bachelor degree or greater	1.688*** (0.318)
% Population Aged 18-44	0.489 (0.504)
% Population Aged 65+	-1.465** (0.700)
% Population Drive to Work Alone	2.439*** (0.320)
% Population 30 Min+ Commute to Work	-2.810*** (0.253)
% Dwellings Owner-Occupied	1.435*** (0.273)
Median Dwelling Value	0.817*** (0.224)
Oregon Incentive (Dummy Variable)	0.082 (0.105)
Constant	-1.418* (0.738)
R^2	0.56
N	12,274

Significance levels: *** p < 0.01; ** p < 0.05; * p < 0.1.

We find that higher hybrid vehicle adoption is associated with Democrat-leaning political preferences, higher household incomes, a higher fraction of the population that have a Bachelor's degree or greater, more people aged between 18 and 44, greater dependence on vehicles for commuting, more owner-occupied dwellings, and higher dwelling values. Lower hybrid vehicle adoption is found for larger household sizes, a greater proportion of people who identify racially as white, more people aged 65+, and more people who have a commute to work of at least 30 minutes. Similarities exist in the determinants of hybrid vehicle adoption and the determinants of solar photovoltaic panel adoption, another clean energy technology where peer effects have been found to be influential (Bollinger & Gillingham, 2012; Graziano & Gillingham, 2014). The adoption of each technology has been associated with regions exhibiting stronger environmental preferences, higher incomes, and fewer people over age 65. Whether interactions exist between these technologies, for example, adoption of solar panels influences the rate of adoption of hybrid (and electric) vehicles (or vice-versa) remains an open question with important implications, most directly for future grid electricity demand.

5 Discussion

This paper contributes to the literature on peer effects in new product diffusion, exploring the effect of peer effects between distinct but related products in the same product category. We demonstrate an instrumental variables approach to identifying peer effects that exploits variation in government incentives, which generalizes to situations where peer effects operate contemporaneously between related products and practices. We find strong evidence of causal peer effects in hybrid vehicle adoption, with each sale of 1 hybrid vehicle eligible for California's hybrid HOV lane incentive leading to the sale of a further 0.461 ineligible hybrid vehicles. Our results suggest that these peer effects are moderated by brand, with stronger within-brand versus between-brand peer effects, emphasizing the importance of timing-of-entry and product mix decisions in the new product diffusion context. While our analysis does not identify the specific pathway(s) through which these peer effects operate, the nature of our local recent-adopter reference group suggests that pathways such as interpersonal communications may be influential in building consumer adoption of hybrid vehicles.

Our findings have important implications for firms and policymakers seeking to accelerate adoption of alternative fuel vehicles. The first is that social influence is an important mechanism in the diffusion of alternative fuel vehicles, as it is with other clean technologies (Bollinger & Gillingham, 2012; Graziano & Gillingham, 2014), suggesting that efforts to build consumer acceptance will lead to increased adoption. Efforts to provide consumers first-hand exposure to new vehicles, such as EV ride-and-drive days, may be enhanced by sharing the experiences of recent adopters. One example of a strategy that has leveraged this influence effectively is a referral program run by EV manufacturer Tesla that provides incentives for owners of Tesla vehicles to market Tesla vehicles to their friends, with rewards for both existing owners (such as Tesla merchandise and tickets to exclusive events) and prospective buyers (a $1,000 discount and free recharging). Second, stronger within-brand peer effects suggest that automakers can benefit from launching multiple models in the same AFV category. Toyota's dominance in the hybrid category can be attributed in part to offering multiple hybrid models, across body styles and including luxury Lexus variants, using peer effects to leverage the success of the Prius across the US automobile market. Third, peer effects have important consequences for automakers' decisions regarding when to enter emerging vehicle categories. While positive between-brand peer effects may allow followers to enter the market relatively more-quickly, stronger within-brand peer effects may allow early entrants to put those followers at a lasting disadvantage.

Our work is not without limitations. First, the strength of our peer effect estimates may not generalize to other product categories. The Toyota Prius is a particularly distinctive product that had a dominant market position during the time period that we study. Other categories may exhibit similar or different peer effects depending on factors such as the observability and relative attractiveness of the available products. Second, the behavior of the population we study may not be representative of the average new vehicle buyer. While our data reflects the purchase decisions of millions of consumers over several years, Californians are known to have relatively stronger preferences for environmental sustainability, and other populations may respond to social exposure about hybrid vehicles differently. Third, while our approach is effective at identifying the causal role of recent adopters, a reference group that we believe to be important, our approach does not address the potentially significant role of the installed base of adopters. When mechanisms other than direct social influence dominate, such as those involving observational learning, instruments may need to be found that include installed base rather than recent sales.

We see many promising opportunities for further study of peer effects in the automotive context, with ongoing policy relevance due to increasing concerns about greenhouse gas emissions and urban air pollution from automobiles. For example, peer effects between related hybrid and electric vehicle categories may be potentially important if they provide a mechanism to influence consumer adoption of fully electric (and potentially zero emission) vehicles. Peer effects may also play a vital role in the diffusion of emerging shared and autonomous vehicle technologies, which challenge long-held social norms about vehicle ownership and use.

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