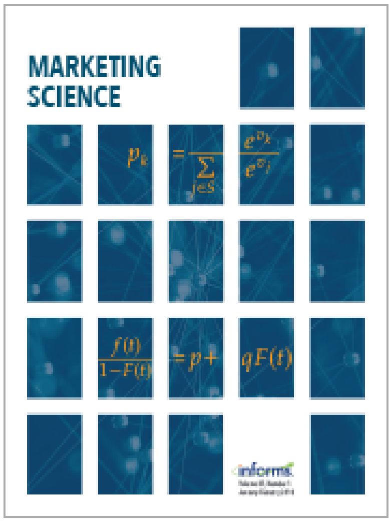

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The End of the Express Road for Hybrid Vehicles: Can Governments' Green Product Incentives Backfire?

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Abstract. In response to growing environmental concerns, governments have promoted products that are less harmful to the environment—green products—through various incentives. We empirically study the impact of a commonly used nonmonetary incentive—namely, the single-occupancy permission to high-occupancy vehicle (HOV) lanes—on green and non-green product demand in the U.S. automobile industry. The HOV incentive could increase unit sales of green vehicles by enhancing their functional value through time saving. On the other hand, the incentive may prove counterproductive if it reduces the symbolic value (i.e., signaling a proenvironmental image) consumers derive from green vehicles. Assessing the effectiveness of green-product incentives is challenging, given the endogenous nature of governments' incentive provisions. To identify the effect of the HOV incentive on unit sales of green and non-green vehicles, we take advantage of HOV-incentive changes in two states, and we employ a multitude of quasi-experimental methods using a data set at the county–model–month level. Unlike previous studies that only examine the launch of the HOV incentive and find an insignificant association between incentive launch and green-vehicle demand, we concentrate on its termination. We find that the *termination* of the HOV incentive decreases unit sales of vehicles covered by the incentive by 14.4%. We provide suggestive evidence that this significant negative effect of HOV-incentive termination is due to the elimination of the functional value the incentive provides: time saving. Specifically, we find that the negative effect is more pronounced in counties where consumers value time saving more (i.e., counties with a longer commute to work and higher income). Additionally, in line with prior literature, the *launch* of the HOV incentive is not found to have a significant effect on green-vehicle sales. Combined, our findings reveal that the effect of termination is not simply the opposite of that of launch, implying that governments' green-product incentives could backfire.

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1. Introduction

Global carbon emissions from fossil fuels—a major driver of climate change—have increased by 82% in the past three decades (Boden et al. 2017). Such growing environmental concerns, along with a heightened sensitivity to dependence on foreign oil, have recently led to a proliferation of sustainability initiatives across the world (e.g., Jenn et al. 2013). Manufacturers in various industries have taken part in these initiatives by developing new products that are less harmful to the environment relative to their extant counterparts. These products are called "green products" because of their use of green technologies that intend to mitigate or reverse the effects of human activity on the environment.[1] For instance, green products such as hybrid vehicles offer solutions to reduce greenhouse-gas emissions, around one-third of which come from the transportation sector in the United States.[2]

Although many consumers express concern for the environment, and green products become more available (Chen and Chang 2012, Chen et al. 2014), green products represent a small fraction of global demand (Chabowski et al. 2011). As a result, federal, state, and local governments have adopted various monetary-incentive programs such as tax credits and rebates to promote green goods and services. Recently, governments have increasingly turned to "free" methods of stimulating green-vehicle demand: nonmonetary incentives such as waivers from high-occupancy vehicle (HOV) lane restrictions. Although only 19 states in the United States adopted monetary incentives as of 2019, a total of 36 states implemented nonmonetary incentives.[3] Despite the prevalence of such nonmonetary incentives, their impact on consumers' adoption of green products remains controversial. Also, little is known about how these incentives influence the demand for products that are not covered by the incentives (e.g., non-green products), as well as other sustainable behavior (e.g., carpooling) (Carley 2011). The lack of empirical evidence on these relationships results in an unclear picture of the effectiveness of governments' nonmonetary green-product incentives in boosting demand for green products and reducing greenhouse-gas emissions.

In this paper, we empirically study the impact of HOV-lane exemptions on consumers' green (i.e., hybrid, plug-in hybrid, and electric) and non-green (i.e., gasoline) vehicle purchases in the U.S. automobile industry.[4] The HOV incentive has been adopted by 15 states in the United States to date, making it one of the most common types of state-level nonmonetary government incentives for green products.[5] On one hand, the HOV incentive could increase unit sales of green vehicles by enhancing their functional value through the time-saving benefit. On the other hand, the HOV incentive may prove counterproductive if it reduces the symbolic value (i.e., signaling a proenvironmental image, or "greenness") consumers derive from buying green vehicles (Dittmar 1992). Signaling greenness through purchases can be particularly strong for sustainable innovations such as hybrid vehicles because (1) these green options typically have inferior functional value relative to their non-green counterparts (e.g., Gneezy et al. 2012); and (2) they are conspicuous products. Indeed, *The New York Times* reported, "it makes a statement about me" as the most important reason for buying a hybrid Prius.[6] The HOV incentive could negatively influence green-vehicle sales driven by the signaling motivation if the incentive renders green vehicles less inferior (or even better) than non-green vehicles in terms of functional value. In such a case, purchasing a green vehicle may produce a weaker (if any) signal of costly proenvironmental behavior in the presence of the incentive. This can, in turn, result in fewer green-vehicle purchases by consumers who aim to signal a green image. As a result of the abovementioned countervailing forces, the direction of the net effect of the HOV incentive on green-vehicle demand is an empirical question.

The research on the effectiveness of government incentives in promoting green-product (or technology) adoption is limited in the marketing literature, despite the recent calls for more marketing studies on sustainability (Sudhir 2016) and public policy (Stewart 2015). One notable exception is Bollinger (2015), which studies the effectiveness of various government policies in the Southern California garment-cleaning industry using counterfactual analyses based on a dynamic structural approach. In the same research stream, Shriver (2015) develops a structural econometric framework incorporating network effects, and he shows that subsidies for fuel retailers in certain geographic markets can be effective in boosting the demand for ethanol-compatible vehicles.[7]

Another research stream that is more directly related to our study exists in energy policy (see Jenn et al. 2018 for a summary of this literature). Papers in this stream have mostly examined the effects of monetary government incentives (e.g., tax waivers) on green-vehicle adoption. These studies have shown that monetary incentives are positively related to green-vehicle adoption (e.g., Gallagher and Muehlegger 2011). In contrast, only a small body of literature has investigated the effectiveness of nonmonetary incentives, such as HOV-lane access, by examining changes in consumer demand around incentive launches. In one of the pioneering studies, Diamond (2009) documents an insignificant relationship between the HOV-incentive launch and hybrid-car market share based on a state–year-level analysis.[8] In line with this finding related to the ineffectiveness of the HOV-incentive launch, Gallagher and Muehlegger (2011) report that, on average, single-occupancy permission to HOV lanes is not significantly correlated with hybrid-car sales based on a state–quarter-level analysis.

Although these studies lay the foundation for understanding important factors related to the effectiveness of nonmonetary green-vehicle incentives, the empirical evidence on the causal effect of the HOV incentive on unit sales of green and non-green vehicles is limited and inconclusive. First, the previously reported insignificant relationship between the HOV incentive and hybrid-car adoption is mostly correlational, as it is based on hedonic regressions using state-level aggregate data. Second, importantly, earlier studies concentrate only on the launch of the HOV incentive. That is, they do not examine the effect of the termination of the HOV incentive, which may not simply be the opposite of the effect of launch. Therefore, they cannot guide policymakers and managers regarding the long-term "net effect" of the HOV incentive. Third, papers in this literature do not investigate the underlying mechanisms for the incentive (in)effectiveness. This is in part because these studies exploit temporal variation using state-level aggregate data, which do not allow for exploiting local-market (e.g., county) characteristics that might affect consumer demand for green vehicles. As a result, previous studies have called for more in-depth studies to take into account and understand more local factors than state-level data (Jenn et al. 2018). Finally, because previous literature has not investigated the effects of the HOV incentive on the demand for non-green vehicles and carpooling behavior, it can provide little guidance on the broader implications of the HOV incentive for overall greenhouse-gas emissions.

In light of these limitations of the extant papers, this study aims to contribute to the literature on the effectiveness of governments' green-product incentives in four ways. First, unlike prior research that has mainly studied the relationship between the HOV-incentive launch and green-vehicle demand, we examine the causal impact of the HOV-incentive *termination* on consumer demand for the green vehicles covered by the incentive. Second, using market characteristics (e.g., commute time) at the local (county) level, we explore possible mechanisms underlying the effect of the HOV-incentive termination. Our quasi-experimental analyses at the county level allow for (1) a stronger case for causal inference, and (2) more detailed insights related to the local heterogeneity in incentive effectiveness than previous studies based on state-level data. Third, importantly, we compare the effect of the HOV-incentive termination with that of launch to investigate the overall effectiveness of the HOV incentive in boosting demand for green vehicles. Fourth, to shed light on the total environmental impact of the HOV incentive, we examine several previously unexplored emissions-related consequences of the incentive, including potential substitution from or to non-green vehicles, market size, and carpooling behavior.

To accomplish these goals, we collect a unique data set that involves county-level vehicle sales around the HOV-incentive terminations and launches in California and Utah. The main empirical challenge in measuring the effect of these incentive changes on vehicle sales is that the assignment of "treatment" (i.e., incentive change) is a strategic decision by state governments, and thus potentially not random. As such, a simple comparison of unit sales between counties in states "treated" by the incentive change and those in "non-treated" states may be misleading, if there are persistent differences (e.g., commute times or preference for green vehicles) across counties in different states.

We address this endogenous incentive-selection issue by employing several quasi-experimental methods using granular analyses at the county–month level. First, we primarily use the difference-in-differences (DiD) approach with coarsened exact matching (CEM) (Iacus et al. 2009) to ensure that treated and nontreated counties are comparable in terms of pretreatment sales trends and several important variables. Specifically, we exploit variables related to policymakers' incentive decisions (e.g., traffic conditions) as well as consumers' green-vehicle purchase likelihood (e.g., income and political inclination) documented in the literature (e.g., Potoglou and Kanaroglou 2007 and Ozaki and Sevastyanova 2011). Besides, the panel nature of our data allows us to control for time-invariant differences across counties via county fixed effects and time-varying differences across vehicle models via model–month fixed effects. Second, we also employ a "border strategy" by leveraging the variation in the HOV incentive around state borders (e.g., Shapiro 2018). To the extent that neighboring counties in the same market, but in different states, are similar in terms of unobserved demographic variables, this strategy complements our primary strategy that relies on matching based on observable demographic variables. Third, we provide a regression-discontinuity-in-time (RDiT)-style analysis (Hausman and Rapson 2017). Assuming that there are no concomitant unobservables influencing unit sales that discontinuously change at the incentive change period, this approach uses a vehicle model's own unit sales in a given county just (e.g., a month) before an incentive change as the counterfactual for those sales just after that incentive change. In line with the identifying assumption underlying the RDiT-style analysis, our subsequent analysis of news articles, as well as the availability of charging stations, reveals no major changes related to infrastructure or other adoption barriers for green vehicles around the incentive changes.

We find that, on average, the HOV-incentive termination decreases unit sales of vehicles covered by the incentive (i.e., hybrid vehicles) by 14.4%. In contrast, on average, green vehicles that are not covered by the HOV incentive (i.e., plug-in hybrid and electric vehicles) and non-green (i.e., gasoline) vehicles do not experience a change in unit sales after the HOV-incentive termination.[9] Additionally, we find that the HOV-incentive termination has an immediate negative effect after the announcement of the termination, and it persists in the medium term (i.e., six months after the incentive termination). These results are robust to an extensive set of robustness checks, including (1) different functional forms, (2) different sets of control variables and fixed effects, (3) falsification exercises, (4) different treatment states (i.e., California versus Utah), (5) differential trends across groups based on matching, (6) alternative treatment dates, and (7) alternative identification strategies.

We then explore potential mechanisms underlying the negative effect of the HOV-incentive termination on unit sales of vehicles covered by the incentive.

Specifically, we investigate whether this negative effect is due to the elimination of the functional value the HOV incentive provides to consumers: time saving. In doing so, we present two types of suggestive evidence that supports the time-saving mechanism. First, we find that the HOV-incentive termination has a more negative sales effect on vehicles covered by the incentive in counties where residents spend more time commuting to work. Second, we show that the negative effect of the HOV-incentive termination is more pronounced in counties with higher income levels. However, we do not find support for a change in symbolic value (i.e., signaling greenness) for the vehicles covered by the incentive in response to the HOV-incentive termination. We also consider several alternative explanations.

Additionally, in line with prior studies, we show that the launch of the HOV incentive leads to only an insignificant 1.61% increase in hybrid-vehicle sales. We provide evidence that this insignificant effect is due to an increase in functional value that is offset by a reduction in symbolic value. Specifically, in support of a raise in functional value, we show that the incentive launch has a positive sales effect on vehicles covered by the incentive in counties with longer commute times. In contrast, the incentive launch has a negative sales effect on vehicles covered by the incentive for those vehicle models and counties that are more conducive to signaling greenness. This finding, combined with the lack of support for a change in symbolic value following the HOV-incentive termination, implies that, although the symbolic value of purchasing a green vehicle covered by the HOV incentive is reduced after the incentive launch, it is not restored after the termination. As a result, the effect of termination is not simply the opposite of that of launch, implying that governments' green-product incentives could backfire.

Finally, we provide additional analyses related to the implications of the HOV incentive for greenhouse-gas emissions. We show that, after the HOV-incentive termination, (1) consumers shift to non-green vehicles with high tailpipe emissions, (2) the market for new cars shrinks, and (3) the percentage of carpoolers increases. As we detail in our conclusion section, collectively, our findings have important implications for policymakers and manufacturers in assessing the effects of governments' HOV incentives on green and non-green product demand, as well as on greenhouse-gas emissions in a comprehensive manner.

2. Background Information and Empirical Context

This section provides details on the incentive changes we study to evaluate the effectiveness of the HOV incentive in stimulating demand for green products and curtailing greenhouse-gas emissions.

2.1. HOV Incentive in California

HOV lanes were constructed to encourage carpooling by providing shorter and more reliable commute times. Before California passed a bill to allow hybrid-vehicle owners to drive solo in HOV lanes, there was excess capacity in those lanes. The reason for this is that the laws at the time limited the HOV-lane access to vehicles with two or more people and motorcycles, and there were not enough carpoolers.[10] To relieve the pressure to convert HOV lanes to general-purpose lanes, state officials looked for ways to shift a small portion of vehicles from congested general-purpose lanes to carpool lanes. This goal, combined with officials' desire to promote less-polluting and more energy-efficient vehicles than conventional cars, led to the launch of the HOV incentive for hybrid vehicles in California.[11] In September 2004, California signed Assembly Bill 2628 to reduce tailpipe emissions. Then-California Governor Arnold Schwarzenegger supported the bill as part of his vision of a "hydrogen highway." This bill, also referred to as the "Yellow Clean Air Vehicle Decals" program, allowed single-occupant use of HOV lanes by hybrid vehicles—the lowest-emission vehicles available at the time. The program started in July 2005. It was initially valid until July 2008, but its termination date was extended twice.

In 2011, the Department of Motor Vehicles (DMV) decided to terminate the incentive for various reasons. First, the DMV aimed to reduce congestion in HOV lanes that started to experience more traffic by terminating the incentive for hybrid cars.[12] California could lose federal highway funding if speeds observed in HOV lanes fell below 45 miles per hour during rush hour, and, therefore, HOV lanes would become "degraded" as defined under federal law.[13] Second, as hybrid cars became popular enough, some believed that the original goal of the incentive was accomplished.[14] Third, the DMV was eventually planning to provide carpool stickers for a new generation of plug-in hybrids, which did not start until September 2012. In May 2011, the California DMV sent letters to the owners of hybrid vehicles to inform them about the termination of Yellow Clean Air Vehicle decals for hybrid vehicles. This program officially ended on July 1, 2011, beyond which hybrid vehicles were no longer allowed to use the HOV lanes without meeting the minimum passenger-number requirement. Importantly, there were no coincident incentive changes for green vehicles other than the HOV-incentive termination for conventional hybrid vehicles around the HOV-incentive termination in California. That said, there was a planned HOV incentive for a new generation of plug-in hybrids, which took effect more than a year after the HOV-incentive termination for conventional hybrids.[15]

2.2. HOV Incentive in Utah

Facing excess capacity in HOV lanes, Utah also passed a similar incentive (Administrative Code 63G-3-102) to promote hybrid vehicles in July 2008.[16] According to this incentive, which became effective in January 2009, hybrid vehicles were allowed single-occupant use of HOV lanes through the "C Plate Permit." Several years after the HOV-incentive launch for hybrid vehicles, the Utah Department of Transportation (UDOT) became concerned with the explosion in the number of vehicles with the C-decal and the potential degradation of its HOV lanes. As a result, UDOT announced the termination of the C Plate Permit for hybrid vehicles starting from May 2011. The program officially expired in July 2011. The termination of the program did not apply to plug-in hybrid and electric vehicles. There were no coincident incentive changes for green vehicles other than the HOV-incentive termination for hybrid vehicles around the HOV-incentive termination in Utah.

With these incentive changes for hybrid vehicles in California and Utah as our backdrop, we examine how the HOV incentive affects unit sales of green vehicles covered by the incentive, green vehicles that are not covered by the incentive, and non-green vehicles.

3. Data and Model-Free Analyses

We combine data from the following 10 sources to assess the impact of HOV-incentive changes in California and Utah on unit sales: (1) a major market research firm, (2) the American Community Survey, (3) the California Air Resources Board, (4) the Office of Energy Efficiency & Renewable Energy, (5) Harvard Kennedy School, (6) the Federal Highway Administration, (7) Factiva, (8) the Alternative Fuels Data Center, (9) the U.S. Energy Information Administration, and (10) California Distributed Generation Statistics (details of these data sources are provided below).

3.1. Sales Data and Market Definition

Our primary data set contains information on business-to-consumer new-vehicle transactions collected by a major market-research firm. We obtained data on every transaction that occurred in a random sample of 15%–20% of the census of new-car dealerships in the United States for the 12-month symmetric window around—that is, 6 months before and after—each incentive change. For each transaction, the data contain the price and detailed characteristics of the vehicle, such as make, model (including trim level), model year, and body type. Also, we observe the customer's ZIP code associated with each transaction. We aggregate these transaction data to the vehicle model–county–month level for our subsequent analyses.[17] In analyzing the sales effects of the HOV incentive for hybrid vehicles, we need to use a clear market definition that allows us to account for market-level shocks. To do so, we follow an approach used in previous studies that examine auto purchases (Mian and Sufi 2012), and we use Core-Based Statistical Areas (CBSAs) to define markets in our data. Defined by the Office of Management and Budget, a CBSA is a U.S. geographic area that consists of one or more counties (or equivalents) anchored by an urban center of at least 10,000 people plus adjacent counties that are socioeconomically tied to the urban center by commuting. Additionally, our analyses concentrate on geographically isolated markets to be able to identify potential customers in a given market. We employ a similar set of criteria to those used by Olivares and Cachon (2009) to determine isolated markets.[18] This leaves us a sample of 275 isolated CBSAs with 1,167 counties, which accounts for around 80% of total unit sales in our original transaction data.

3.2. Supplementary Sources of Data

Our second source of data consists of the American Community Survey,[19] which provides annual county-level information on demographic variables. Specifically, we collect demographic data on income (median household income), education (the percentage of population with a bachelor's degree or higher), gender (the percentage of male population), age (the median age of household head), unemployment rate, and commute times (mean travel time to work in minutes). We exploit these variables to (1) match counties that are affected by the incentive change with those that are not (as discussed later in detail), and (2) examine the potentially heterogeneous impact of the HOV incentive across different demographics. The American Community Survey also includes annual county-level data on the percentage of carpoolers, which we use to study the relationship between the HOV incentive and carpooling behavior. In addition, we obtain data on emission levels at the county–month level from the California Air Resources Board to examine emission patterns around the HOV-incentive termination in California. We also collect greenhouse-gas emission levels (grams per mile) at the vehicle-model level from the Office of Energy Efficiency & Renewable Energy (https://www.fueleconomy.gov) to explore the heterogeneity in the sales effects of the HOV incentive by vehicle emission levels. We then convert greenhouse-gas emission levels to a categorical (i.e., low, medium, and high) measure for vehicle emission based on the terciles of emission levels at the vehicle-model level.

Data on the election statistics of 2004, 2008, and 2012 presidential elections come from the Harvard Kennedy School.[20] In particular, we collect data on the county-level percentage of votes for the Democratic Party as a proxy for the support of green technologies, given that the Democratic Party intends for the United States to become a clean-energy superpower.[21] We use this variable in our matching procedure as well as in our analyses on the heterogeneous effects of the HOV incentive. To supplement the previously mentioned matching variables, we also acquire information on traffic congestion (i.e., average daily traffic volume) at the state level from the Federal Highway Administration.

We rely on the Factiva news database to extract data on newspaper articles about green vehicles in California and Utah. This data set allows us to track whether there are any major changes related to infrastructure or other adoption barriers for green vehicles around HOV-incentive changes. To complement this news search, we also obtain data on the number of charging stations (public and private) at the county–month level from the Alternative Fuels Data Center (https://afdc.energy.gov). We use this variable to assess the patterns in charging-station availability and to explicitly control for its potential effect on unit sales of vehicles in our analyses. To control for the impact of gas prices on vehicle sales, we obtain state–month-level gas prices from the U.S. Energy Information Administration.[22] Finally, we also collect data on all the installations of interconnected solar photovoltaics (PV) net energy metering (NEM) systems (i.e., NEM Currently Interconnected Data Set) in a given county from California Distributed Generation Statistics. Based on the terciles of the number of solar PV installations, we create a categorical measure to proxy the level of social desirability of being seen as "green."

3.3. Raw Sales Patterns Around the HOV-Incentive Termination

Table 1 provides descriptive statistics for key variables used in our analyses of the HOV-incentive termination. It also shows the raw "difference-in-differences" in terms of percentage changes in unit sales for green vehicles covered by the HOV incentive, green vehicles that are not covered, and non-green (i.e., gasoline) vehicles for counties that are affected by the incentive termination (i.e., treatment group) and those that are not (i.e., control group).[23] These raw data patterns show that, after the incentive termination, unit sales of green vehicles covered by the incentive decreased more in treated counties relative to control counties. On the other hand, the differences in percentage unit-sales changes between the treatment and control groups were much smaller and insignificant for the vehicles that are not covered by the HOV incentive. We use econometric analyses to formalize these insights in Section 4.

3.4. Other Potential Changes Around the HOV-Incentive Termination

In Online Appendix C, we examine other potential changes around the HOV-incentive termination that might confound the relationship between vehicle sales and the termination of the HOV incentive. We first investigated whether there was any sudden change in the number of charging stations. We found that the availability of charging stations did not change sharply around the HOV-incentive termination. We account for the gradual changes in the number of charging stations by explicitly controlling for it in our subsequent econometric analyses. Furthermore, following the approach used by earlier marketing studies (e.g., Tirunillai and Tellis 2017), we searched for news articles on Factiva for potential news about major changes related to infrastructure or other adoption barriers for green vehicles in California and Utah. The search results did not provide any evidence of major changes around the HOV-incentive termination.

4. Effect of the HOV-Incentive Termination on Consumers' Green-Vehicle Adoption

This section examines the main effect of the HOV-incentive termination on unit sales of green vehicles covered by the HOV incentive, green vehicles that are not covered, and non-green vehicles. The key empirical challenge in identifying the causal effect of governments' green-vehicle incentives is that the termination of the incentive may not be exogenous. In particular, as mentioned in Section 2, policymakers' incentive decisions may be influenced by state-specific factors such as traffic conditions, commute times, residents' preferences for green products, and the demographic composition of each state. Thus, a simple comparison of unit sales between counties in states with an incentive change and those in unaffected states may be misleading. To address this identification challenge, we employ several identification strategies that rely on different identifying assumptions.

4.1. Empirical Strategy: DiD with Coarsened Exact Matching

Because the availability of the HOV incentive varies over time, and these incentive changes apply only to a subset of vehicles (i.e., hybrid cars) in a subset of counties (e.g., those in California), we can use a DiD identification strategy to estimate the main effect of

Table 1. Descriptive Statistics and Raw Data Patterns

Variables	Number of observations	Mean	Standard deviation	Maximum	Minimum	Counties with incentive termination	Counties without incentive termination	Difference (p-value of t-test)
County–vehicle model–month-level variables								
Green vehicles covered by the HOV incentive								
Price (in thousands USD)	7,420	35.0	5.4	46.5	16.9			
Unit sales	7,420	1.3	4.7	95	0.0			
Green vehicles not covered by the HOV incentive								
Price (in thousands USD)	232	41.0	4.7	55.1	32.6			
Unit sales	232	1.6	2.0	13	0.0			
Gasoline vehicles								
Price (in thousands USD)	77,713	35.3	16.9	198.3	10.0			
Unit sales	77,713	1.9	4.6	124	0.0			
State-month level variable								
Gas price (USD)	1,800	3.6	0.2	4.5	2.9			
County–year-level demographics								
Income: median household income (in thousands USD)	3,501	50.3	10.4	101.6	22.1			
Education: Percent bachelor's degree or higher achievement	3,501	22.9	9.3	58.3	4.6			
Commute: Mean travel time to work (in minutes)	3,501	24.6	4.8	44.2	14.5			
Political inclination: Percent votes for the Democratic party	3,501	41.8	16.8	90.0	10.1			
Gender: Percent male residents	3,501	50.0	2.4	72.7	36.0			
Age: Median age	3,501	37.4	1.5	41.7	32.6			
Unemployment: Percent unemployment rate	3,501	9.2	3.1	22.9	1.5			
Percent of carpoolers	3,501	0.11	0.02	0.21	0.05			
State–year-level variable								
Average daily traffic volume	150	4,841	2,159	9,223	1,211			
Categorical vehicle model level variable								
Emission level (percentage occurrence)	403	High, 42.9%; medium, 44.2%; low, 12.9%						
Model-free evidence for the HOV-incentive termination								
Percent unit sales change for green vehicles covered by HOV incentive after termination						–18.1%	–7.6%	–10.5%* (0.03)
Percent unit sales change for green vehicles not covered by HOV incentive after termination						2.0%	4.7%	–2.7% (0.74)
Percent unit sales change for gasoline vehicles after termination						8.3%	7.1%	1.2% (0.89)

*$p < 0.05$.

each incentive change on unit sales. More precisely, we estimate the effect of a given incentive change on unit sales by comparing changes in unit sales before and after the incentive change takes effect in a given county (i.e., treatment group) with a baseline of changes in unit sales in counties with no incentive change (i.e., control group) in the same period. In other words, when estimating the average effect of the HOV-incentive termination, the treatment group consists of counties where the HOV incentive becomes unavailable (i.e., counties in California and Utah); and the control group includes counties where the HOV incentive is in effect throughout our observation window (i.e., counties in Arizona, Colorado, Florida, Tennessee, New York, and Virginia).

The main identifying assumption of the DiD approach discussed above is that there are no unobserved, time-varying, county-specific variables that are correlated with both the incentive change and unit sales. To alleviate the potential concerns related to this assumption, we primarily rely on two supplemental approaches. First, we show that accounting for (1) important control variables (e.g., price and the number of charging stations), (2) unobserved county-specific time-invariant factors (e.g., preference for green products), (3) unobserved strata-specific time trends (e.g., changes in local economic conditions), and (4) unobserved time-varying factors specific for a given vehicle model but common across all counties (e.g., national advertising) do not change the estimated effect substantially. Therefore, the effect of any remaining unobservables would need to be relatively large compared with the factors we account for to result in a significant change in our qualitative findings.

Second, to further lessen the endogeneity concern, we combine the DiD with matching (see Singh and Agrawal 2011 and Zervas et al. 2017 for a similar approach). Intuitively, the goal of the matching procedure is to generate similar treated and control counties based on a set of observables to reduce the potential for unobservable differences between the two groups. Specifically, we apply the coarsened exact matching method in our main analyses (Iacus et al. 2009). To do so, we stratify counties based on observable characteristics related to policymakers' termination decisions, including local traffic conditions and commute times (as discussed in Section 2), as well as local preferences for green vehicles. Previous studies document several characteristics that distinguish U.S. consumers who have a high preference for green vehicles—green consumers—from those who do not (e.g., Potoglou and Kanaroglou 2007 and Ozaki and Sevastyanova 2011). In particular, green consumers are more likely to have higher income and education levels. They are also more likely to be older females and to vote for the Democratic Party. As a result, we use income, education, gender, age, and political inclination, along with traffic conditions and commute times, as matching variables to generate strata.[24]

Our matching procedure results in 21 strata for the HOV-termination analysis. We conduct t-tests to see whether counties in treatment and control groups are comparable in terms of the matching characteristics. Specifically, we perform a stratified t-test of the difference in the average of a given matching variable (e.g., income) between the two groups. None of the t-tests for all matching variables reject the null hypothesis that the two groups have the same average at the 5% significance level. The results of these t-tests suggest that the counties in treatment and control groups are largely comparable in terms of key observables. Therefore, the variation in the treatment status (i.e., incentive change) across counties within the same stratum will allow us to identify the average effect of the HOV-incentive termination.

In our subsequent analyses on the HOV-incentive termination effect, we rely on a count data model—namely, the fixed-effects negative binomial model—as our main specification. This is because our dependent variable (unit sales at the county–vehicle–month level) takes on the value zero for many observations in our data, especially for green vehicles. This is reflected in the summary statistics, which show a mean of 1.3 for unit sales of green vehicles covered by the HOV incentive. Faced with similar count variables as the dependent variable, previous literature modeling consumer demand in marketing has used count models, including the negative binomial and Poisson regressions (e.g., Busse et al. 2010, Wang and Goldfarb 2018, and Ozturk et al. 2019). We later show that our findings are robust to alternative specifications, such as a log-linear regression model, as well as a Poisson model.

4.2. The Effect of HOV-Incentive Termination on Unit Sales

In this subsection, we estimate the average effect of HOV-incentive termination on unit sales. We estimate this effect separately for three types of vehicles: green vehicles covered by the incentive (i.e., hybrid vehicles), green vehicles that are not covered (i.e., plug-in hybrid vehicles and electric vehicles), and non-green vehicles (i.e., gasoline vehicles).[25] Our unit of analysis is county (i)–vehicle model (j)–month (t), for example, New York county–Toyota Prius–August 2011. Given that our dependent variable—that is, unit sales—is a count variable, we identify the effect of interest by using the following negative binomial model with log link:

$$\ln(UnitSales_{ijt}) = \beta_{HOV\,term} HOVtermination_{it} + \alpha_i + \delta_{s(i)j} + \lambda_{jt} + \boldsymbol{X}'_{ijt}\gamma + \varepsilon_{ijt}. \quad (1)$$

The dummy variable $HOVtermination_{it}$ is equal to one after the HOV-incentive termination is announced if a given county belongs to a state where there is an HOV-incentive termination, and zero otherwise.[26] County fixed effects, α_i's, capture time-invariant unobserved factors of each county, such as the location of the market. $s(i)$ is the stratum s to which county i belongs, which is determined by the CEM algorithm, as explained in Subsection 4.1. Accordingly, $\delta_{s(i)j}$ is the stratum-vehicle fixed effect, which captures the baseline demand of a given vehicle model j for a given stratum. Vehicle model–month dummies, λ_{jt}'s, allow us to control for vehicle–month-specific unobservables, such as manufacturer-level advertising, as well as promotions to dealers and consumers (see Ozturk et al. 2016 for a similar approach). Note that as λ_{jt} subsumes vehicle model fixed effects, it also accounts for vehicle model-specific factors that do not vary over time, such as manufacturer (e.g., GM), brand (Chevrolet), and nameplate (e.g., Volt). Because λ_{jt} subsumes month fixed effects, it also takes into account time-varying factors that might impact demand common to all vehicle models and counties such as consumer confidence in the economy (e.g., Ozturk et al. 2019). The vector $\boldsymbol{X_{ijt}}$ consists of county-, vehicle model-, and/or month-varying control variables. It includes the following annual county-level demographic variables: income, education, age, gender, unemployment rate, and mean travel time to work. The vector $\boldsymbol{X_{ijt}}$ also involves the average transaction price of a vehicle model j in county i in month t, monthly average gas price in each state, and the number of charging stations at the county–month level.

The coefficient of interest in Equation (1) is $\beta_{HOVterm}$. Because there are no other coincident incentive changes for green vehicles in our analysis period, as mentioned in Section 2, we interpret $\beta_{HOVterm}$ as the average effect of the HOV-incentive termination on unit sales. As we conduct separate analyses for green vehicles covered by the incentive, green vehicles that are not covered, and non-green vehicles, we obtain three different coefficients (one for each vehicle type). For instance, when we use $\ln(UnitSales_{ijt})$ for green vehicles covered by the incentive as our dependent variable; if $\beta_{HOVterm}$ is smaller than zero, we interpret it as indicating that the average unit sales for green vehicles covered by the incentive decreases by $100 \times [1 - \exp(\beta_{HOVterm})]\%$ after the HOV incentive is terminated. Similarly, when we use $\ln(UnitSales_{ijt})$ for non-green vehicles as our dependent variable, if $\beta_{HOVterm}$ is greater than zero, we interpret it as indicating that the average unit sales for non-green vehicles increases by $100 \times [\exp(\beta_{HOVterm}) - 1]\%$ after the HOV incentive is terminated.

4.2.1. Identification Check. Before we proceed to the estimation of the average effect of the HOV-incentive termination on unit sales, we perform an identification check to examine whether our empirical strategy can recover the causal sales effect of the incentive change. Specifically, we estimate Equation (1) with a slight modification by splitting our main independent variable ($HOVtermination_{it}$) into a sequence of dummy variables for the months before and after the treatment (see Wang and Goldfarb 2018 for a similar approach). The base month is six months before the implementation of the program.

In Figure 1, we plot the coefficients associated with these monthly dummy variables to examine the parallel-trends assumption of our DiD identification strategy on unit sales of green vehicles covered by HOV-incentive termination. The solid line shows the estimated coefficient for each month, and the bars show the 95% confidence interval for each coefficient.

Figure 1. The Impact of HOV-Incentive Termination on Green Vehicles Covered by the Incentive

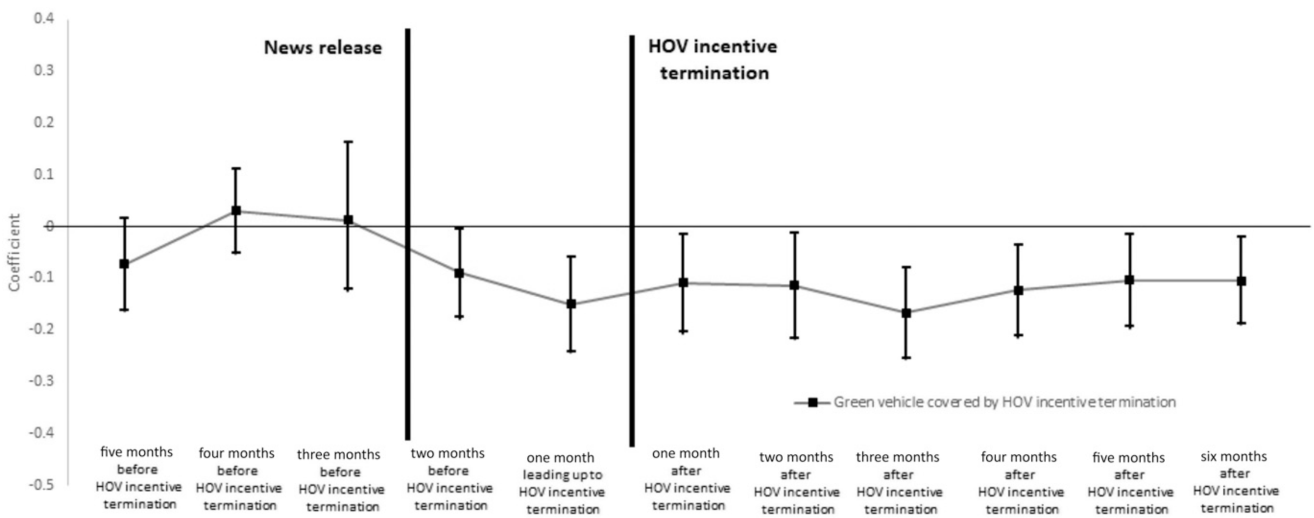

Figure 2. (Color online) The Impact of HOV-Incentive Termination on Vehicles Not Covered by the Incentive

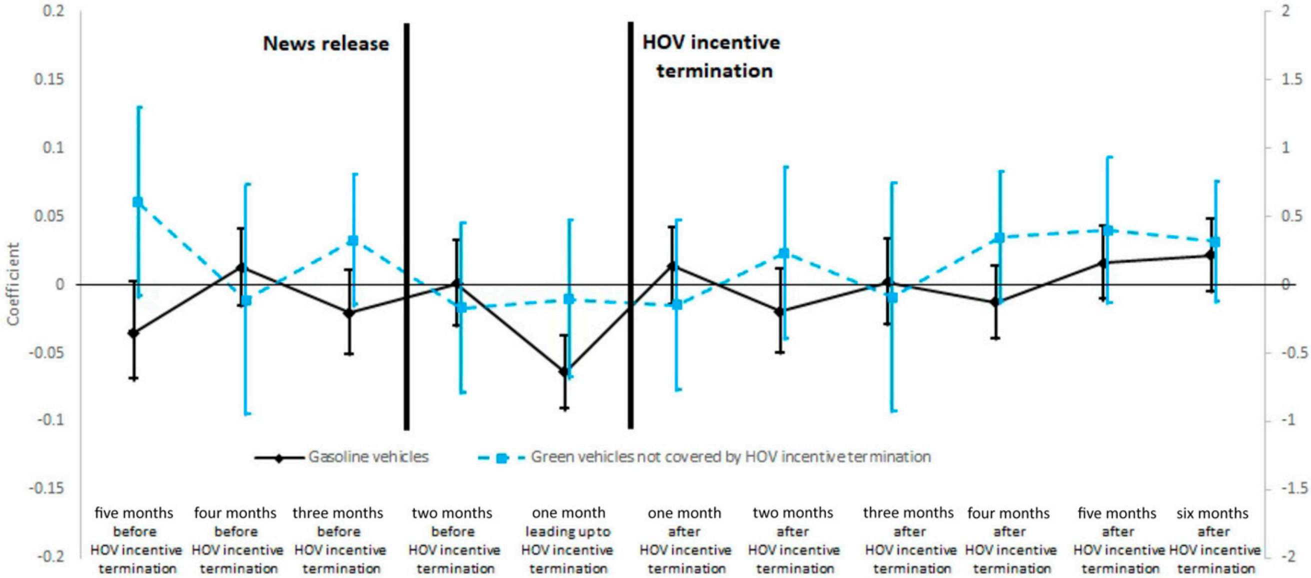

Figure 2 shows the coefficients associated with these monthly dummy variables for green vehicles not covered by HOV-incentive termination and gasoline vehicles. These two graphs show that the estimated coefficients are insignificant before the treatment, which indicates that pretrends in unit sales are comparable between the treatment and control groups after controlling for the covariates and fixed effects in our main specification. Although no identification test is conclusive, as with any quasi-experimental analysis, this identification check supports our empirical strategy.

4.2.2. Main Effect. The columns in Table 2 present the estimated effect of the HOV-incentive termination on unit sales of green vehicles covered by the incentive (i.e., hybrid vehicles), green vehicles that are not covered (i.e., plug-in-hybrid vehicles and electric vehicles), and non-green vehicles (i.e., gasoline vehicles) using Equation (1). The estimates in column (1) suggest that the average effect of the HOV-incentive termination on unit sales of green vehicles covered by the incentive is negative (−0.155) and statistically significant ($p < 0.01$), which amounts to a 14.4% [1 − exp(−0.155)] decrease in unit sales in response to the HOV-incentive termination.[27] On the other hand, as shown in columns (2) and (3), we do not find a statistically significant effect of the termination of the HOV incentive on unit sales of green vehicles that are

Table 2. The Impact of HOV-Incentive Termination on Unit Sales of Different Vehicle Types

Dependent variable: Unit sales	(1) Green vehicles covered by the incentive	(2) Green vehicles not covered by the incentive	(3) Gasoline vehicles
HOV incentive termination	−0.155**	0.041	0.005
	(0.062)	(0.118)	(0.020)
Price	−0.015*	0.051+	−0.022***
	(0.008)	(0.031)	(0.001)
Stratum × vehicle model dummies	Yes	Yes	Yes
County dummies	Yes	Yes	Yes
Vehicle model × month dummies	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Number of observations	7,420	1,232	77,713
Log likelihood	−6,453	−1,235	−107,937

Notes. This table displays the results based on Equation (1), which measures the average sales effect of HOV-incentive termination on green vehicles covered by the incentive change (i.e., hybrid vehicles), green vehicles not covered by the incentive change (i.e., plug-in hybrid vehicles and electric vehicles), and gasoline vehicles. Clustered standard errors (county) are reported in parentheses. Control variables include state–month-level average gasoline price, county–month-level number of charging stations, and county-level demographic variables that change annually: income, education, age, gender, unemployment rate, and commute.

$^{+}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

not covered by the incentive (−0.041, $p = 0.73$) and non-green vehicles (0.005, $p = 0.82$). In sum, the estimation results indicate that the HOV-incentive termination hurts the adoption of green vehicles covered by the incentive. However, on average, we do not find significant evidence of a demand spillover to vehicles that are not covered by the incentive change.

We also investigate whether the negative effect of the HOV-incentive termination on covered green vehicles is persistent over time. Recall that we created month-specific treatment coefficients in our earlier discussions of identification checks, and we used Figure 1 to compare pretreatment trends between the treatment and control groups. We can examine the months after the HOV-incentive termination in these figures to see whether the effects vary over time. The coefficient for the HOV-incentive termination is negative and significant for green vehicles covered by the incentive across all months following the announcement (i.e., confidence intervals do not cover zero).

4.3. Robustness Checks

To further strengthen the causal interpretation of our previous findings, as suggested in Goldfarb and Tucker (2014), we investigate a set of robustness checks including (1) different functional forms, (2) falsification exercises, (3) different treatment states for the HOV-incentive termination (i.e., California versus Utah), (4) differential trends across strata, and (5) alternative treatment dates.

We first check the robustness of our findings to other functional forms. Our main specification in Equation (1) uses a negative binomial with log-link to estimate the effect of incentive changes on unit sales. To examine the sensitivity of our results, we reestimate the effect using Poisson and log-linear regression models in Table E.2 in Online Appendix E. These estimates show a significant decrease of 18.6% and 8.1% for Poisson and log-linear models, respectively. These results are consistent with our earlier findings for the HOV-incentive termination. We also check the robustness of our results to falsification exercises, different treatment states for the HOV-incentive termination (i.e., California versus Utah), differential trends across strata, and alternative treatment dates in Online Appendix E. The results from these sensitivity analyses are in line with our earlier findings.

4.4. Alternative Identification Strategies

We also conduct analyses using other identification strategies—that is, the border and the RDiT strategies—that complement our main empirical strategy based on DiD with CEM.

4.4.1. Border Strategy. The DiD approach uses the unit sales in counties that are not affected by an incentive change as counterfactual unit sales for counties that are treated by that incentive change. Although we use CEM to ensure that treatment and control groups are comparable in terms of a set of observable characteristics, there may still be differences between the two groups in terms of unobservable characteristics. To allay this worry, we employ the "border strategy" by leveraging the variation in green-vehicle incentives around state borders (e.g., Shapiro 2018).

In this strategy, counties in a state without the HOV-incentive termination will serve as controls for counties within the same market, but on the other side of the border in another state where the incentive is terminated. As such, we will attribute the unit-sales difference for a given vehicle type between neighboring counties in different treatment conditions to the HOV-incentive termination. To the degree that neighboring counties in the same market, but in different states, are comparable in terms of unobserved characteristics, this border strategy supplements our primary empirical strategy that relies on matching based on observable demographic variables. The details of our analyses based on the border strategy are provided in Online Appendix F. The estimation results based on the border strategy are provided in Table F.1 in the online appendix. The coefficient for the HOV-incentive termination is negative and significant for the vehicles covered by the incentive, supporting our earlier results based on the DiD with CEM.

4.4.2. Regression-Discontinuity-in-Time-Style Analysis. In our estimations so far, we have used a vehicle model's unit sales in a county without the HOV-incentive termination as the counterfactual for unit sales of the same vehicle model in a similar county that is affected by the incentive termination. An alternative way to generate counterfactual unit sales is to use a vehicle model's unit sales just before the HOV-incentive termination as the counterfactual for those just after the termination. The key identifying assumption of this approach is that there are no concomitant unobservables influencing unit sales that discontinuously change at the start of the incentive termination, which is supported by our earlier analyses discussed in Subsection 3.4. To further reduce the possibility of time-varying unobservables that sharply change in the close temporal vicinity of the HOV-incentive termination, it is crucial to concentrate on a narrow window around the incentive change. This idea of narrowing the temporal windows around the focal incentive change was used by previous marketing studies to alleviate the concern about time-varying unobservables (e.g., Ozturk et al. 2016).

As we implement this identification strategy as a complementary approach to our primary empirical strategy, we do not provide a complete set of analyses required by RDiT (see Hausman and Rapson 2017). As such, we call the associated analysis an RDiT-style analysis. Specifically, we rely on a local linear strategy where we use various relatively narrow time windows—that is, 4 weeks, 8 weeks, 12 weeks, and 16 weeks before and after each incentive change—to examine the effect of HOV-incentive termination on unit sales of different vehicle types. The details of our analyses based on the RDiT strategy are provided in Online Appendix G. Table G.1 in the online appendix shows the local linear estimation results for the impact of the HOV-incentive launch and termination. The estimates suggest that our earlier findings are robust to the RDiT-style analysis.

5. Mechanism

Our results so far show that the adoption of green vehicles covered by the incentive is negatively influenced by the HOV-incentive termination. This section investigates various mechanisms through which the HOV-incentive termination affects the adoption of green vehicles covered by the incentive. We argue that the HOV incentive influences consumer demand via a mechanism related to the functional value it provides: time saving. The HOV incentive is expected to be more effective for consumers that seek a time-saving benefit. Therefore, if time saving is the underlying mechanism, we anticipate a larger drop in hybrid-vehicle sales in response to the HOV-incentive termination in counties where consumers value time saving more. In what follows, we provide suggestive evidence that supports this time-saving mechanism. We then rule out several alternative explanations.

The key benefit of the HOV incentive is that the unrestricted access to HOV lanes significantly reduces travel time for drivers. Some have seen their commuting times halved. Therefore, one would expect that the HOV-incentive launch would result in more green-vehicle sales covered by that incentive for consumers that value time saving more. On the flip side, the HOV-incentive termination would likely have a more negative effect on green-vehicle adoption for consumers that value time saving more. To establish that the time-saving mechanism is at work, we provide the following suggestive evidence. First, we provide evidence that the HOV-incentive termination has a more negative sales effect on vehicles covered by the incentive in counties where residents spend more time commuting to work. Second, we show that the HOV-incentive termination has a more negative sales effect on vehicles covered by the incentive in counties with higher income levels. Along with their inherent value in better understanding the effectiveness of governments' green vehicle incentives, these mechanism checks aim to "help make casual identification more convincing" (Goldfarb and Tucker 2014, p. 31).

5.1. HOV-Incentive Termination Has a More Negative Impact in Counties with a Longer Commute to Work

The benefit of having access to the HOV lane is more for consumers who have longer commutes. As a result, we expect that the impact of the HOV-incentive termination will be more negative in counties where residents spend more time traveling to work. To assess this conjecture, we estimate the following specification:

$$\begin{aligned}\ln\left(UnitSales_{ijt}^{covered\_green}\right) &= \mu HOVtermination_{it} \\ &\quad + \mu_{Commuteint}^{HOV} HOV\ termination_{it} \times Commute_{it} \\ &\quad + \alpha_i + \delta_{s(i)j} + \lambda_{jt} + \boldsymbol{X}_{ijt}'\gamma + \varepsilon_{ijt}. \qquad (2)\end{aligned}$$

$Commute_{it}$ is the county-level mean travel time to work. $\mu_{Commuteint}^{HOV}$ measures the heterogeneous (if any) impact of the HOV-incentive termination on unit sales of green vehicles covered by the incentive in terms of the commute level in a given county. The fixed effects and control variables are the same as those defined for Equation (1). Column (1) in Table 3 provides the coefficient estimates for the specification above. The coefficient of the $HOVtermination_{it} \times Commute_{it}$ interaction is negative and significant (-0.049, $p < 0.01$), which suggests that the reduction in unit sales for the green vehicles covered by the incentive in response to the HOV-incentive termination becomes more substantial as commute to work increases.[28]

5.2. HOV-Incentive Termination Has a More Negative Impact in Counties with Higher Income

Previous literature points out that consumers with higher income value their time more because of its opportunity cost (e.g., Stigler 1961). Similarly, Cesario (1976) shows that drivers with higher income value reducing the commuting time more. Therefore, we expect that the impact of the HOV-incentive termination will be more negative in counties with higher income. To formally examine this prediction, we use the following specification:

$$\begin{aligned}\ln\left(UnitSales_{ijt}^{covered\_green}\right) &= \mu HOVtermination_{it} \\ &\quad + \mu_{Commuteint}^{HOV} HOVtermination_{it} \times Commute_{it} \\ &\quad + \mu_{Incomeint}^{HOV} HOVtermination_{it} \times Income_{it} \\ &\quad + \alpha_i + \delta_{s(i)j} + \lambda_{jt} + \boldsymbol{X}_{ijt}'\gamma + \varepsilon_{ijt}. \qquad (3)\end{aligned}$$

The parameter of interest in this specification is $\mu_{Incomeint}^{HOV}$. It measures the heterogeneous (if any) impact of the HOV-incentive termination on unit sales of green vehicles covered by the incentive in terms of the median household income in a given county. The fixed effects and control variables are the same as those defined for Equation (1). Column (2) in Table 3 presents the coefficient estimates for the specification above. The negative and significant coefficient of the $HOVtermination_{it} \times Income_{it}$ interaction ($\mu^{HOV}_{Incomeint} = -0.017$, $p < 0.05$) suggests that the reduction in unit sales for the green vehicles covered by the incentive in response to the HOV-incentive termination is more in counties with higher income relative to those with lower income.

5.3. Other Interactions and Alternative Explanations

5.3.1. Symbolic Value. The HOV incentive could be counterproductive if it reduces the symbolic value consumers derive from buying green vehicles. Previous research has shown that the purchase of new goods is a way to symbolize personal and social identities and values, especially for conspicuous products such as cars (Dittmar 1992). Specifically, earlier studies suggest that some car buyers purchase hybrid cars (or sustainable innovations in general) to signal a proenvironmental identity or image—that is, greenness (Noppers et al. 2014). These signals can be particularly strong for sustainable innovations such as hybrid vehicles because these green options typically have inferior functional value (e.g., higher prices or behavioral costs) relative to their non-green counterparts (e.g., Gneezy et al. 2012). The increase in the functional value offered by green vehicles because of the HOV incentive could negatively influence green-vehicle sales driven by the signaling motivation. This is because the incentive could render green vehicles less inferior (or even better) than non-green vehicles in terms of functional value. Accordingly, buying a green vehicle could provide a weaker (if any) signal of costly proenvironmental behavior when the HOV incentive is in effect. This can, in turn, lead to fewer green-vehicle purchases by consumers who want to signal a green image. Such a potential reduction in symbolic benefits can be crucial. Some studies have shown that evaluations of symbolic attributes are the only significant factor explaining the adoption of sustainable innovations, whereas evaluations of functional attributes did not explain actual adoption when the evaluation of symbolic attributes are taken into account (Noppers et al. 2016).

The preceding discussion suggests that the termination of the HOV incentive may result in increased symbolic value for hybrid vehicles as they lose the incentive-driven functional value once the incentive is removed. If there is an increase in the symbolic value of covered green vehicles after the termination of the HOV incentive, then our estimates related to the time-saving mechanism could be biased toward zero. To assess whether a change in symbolic value after the termination could confound our earlier findings, we add an interaction term related to the potential for signaling greenness in Equation (3): $HOVtermination_{it} \times Greenversiononly_j$. The $Greenversiononly_j$ is a dummy variable that takes on value one for hybrid vehicle models that do not have a non-green (i.e., gasoline) counterpart (e.g., for Toyota Prius), and zero otherwise (e.g., for Toyota Camry). As previous research suggests that some consumers would like to be seen driving an explicitly green vehicle such as the Toyota Prius (Gallagher and

Table 3. Possible Mechanisms

Dependent variable: Unit sales	(1) Commute	(2) Income	(3) Symbolic value	(4) Other demographics
HOV incentive termination	1.108**	1.928***	1.938***	3.569
	(0.400)	(0.533)	(0.535)	(6.189)
HOV incentive termination × Commute	−0.049**	−0.040**	−0.040**	−0.039⁺
	(0.021)	(0.019)	(0.018)	(0.023)
HOV incentive termination × Income		−0.017*	−0.017*	−0.018*
		(0.007)	(0.008)	(0.009)
HOV incentive termination × Green version only			−0.024	−0.023
			(0.079)	(0.083)
Other interactions	No	No	No	Yes
Dummies: *Stratum × vehicle model*, *county*, *vehicle model × month*	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes
Number of observations	7,420	7,420	7,420	7,420
Log likelihood	−6,452	−6,451	−6,450	−6,448

Notes. Clustered standard errors (county) are reported in parentheses. Control variables include vehicle price, state–month-level average gasoline price, county–month-level number of charging stations, and county-level demographic variables that change annually: income, education, age, gender, unemployment rate, and commute. Interactions with other demographics (not reported because of space constraints) include interactions of the incentive termination with the remaining demographics that are part of our control variables.

$^+p < 0.1$; $^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Muehlegger 2011), $Greenversiononly_j$ is used to proxy the potential of a given vehicle model for signaling greenness. As shown in column (3) in Table 3, the $HOVtermination_{it} \times Greenversiononly_j$ interaction is insignificant. Therefore, we do not find support for a change in symbolic value following the termination of the HOV incentive.

As an additional robustness check for the insignificant change in symbolic value, we use the dummy variables $MediumSolar_i$ and $HighSolar_i$ that represent counties with medium and high levels of solar PV installations (see subsection 3.2 for the details of this measure). These variables proxy the level of social desirability of being seen as green. Thus, they can be seen as a measure of the potential of a given county for signaling greenness. When we add the interaction terms $HOVtermination_{it} \times MediumSolar_i$ and $HOVtermination_{it} \times HighSolar_i$ to the specification estimated in column (3) in Table 3, we find that the coefficients of both interactions are insignificant. In line with our earlier results, this finding provides no evidence of a change in symbolic value after the HOV-incentive termination. One possible explanation for the lack of change in symbolic value is that, even after the termination of the HOV incentive, there will be hybrid vehicles on the road that were purchased during the HOV-incentive period because of the increased functional value. Therefore, it will still be difficult to signal greenness to others even after the incentive ends.

5.3.2. Interactions with Other Demographics. To allay concerns related to the potential moderating effects of other demographic variables on the relationship between HOV-incentive termination and unit sales, we also control for additional interactions. Specifically, we include the interactions of income, education, age, gender, and unemployment rate with the HOV-incentive termination in Equation (3) and report the estimates for our key interactions in column (4) of Table 3.[29] Our previous findings remain robust to the inclusion of these additional interactions.

5.3.3. Pending Availability of an HOV Incentive for Plug-in Hybrids. As mentioned in Subsection 2.1, the DMV was planning an HOV incentive for a new generation of plug-in hybrids in California, which eventually started more than a year after the HOV-incentive termination for conventional hybrids. Therefore, one could argue that some consumers might decide to wait for that pending incentive following the termination of the HOV incentive for conventional hybrids.[30] To assess the potential implications of this feature of our setting on our key finding, we perform a new analysis using aggregate future sales for plug-in hybrid vehicle models by county. If the above explanation were at work, one would expect to see a larger sales decline following the HOV-incentive termination in counties where there are more plug-in vehicle sales after the pending HOV incentive takes effect for plug-in hybrids. To see whether this is the case, we created a variable that indicates total sales of plug-in hybrid vehicles by county during the six months following the launch of the HOV incentive for plug-in hybrid vehicles (September 2012–February 2013). We then include the interaction of this variable with our HOV-termination dummy in Equation (3) along with all other interactions discussed earlier. If this new interaction were significant and negative, it could provide support for the explanation above. However, this interaction coefficient is positive (0.069) and insignificant (p = 0.48), which is not in line with the above explanation.[31]

6. Overall Effectiveness of the HOV Incentive in Boosting Green-Vehicle Demand and Reducing Emissions

Our results so far indicate that the termination of the HOV incentive led to a reduction in green-vehicle sales covered by the incentive via the time-saving mechanism. However, previous literature has documented that the launch of the HOV incentive has an insignificant (or even negative) relationship with green-vehicle demand (Diamond 2009, Gallagher and Muehlegger 2011). Combined, these findings raise the following questions: Can the net effect of the HOV incentive on the unit sales covered by the incentive be negative? To the extent that the net effect is negative, does that mean that the HOV incentive could result in more carbon emissions? Given that state governments aim to increase the sales of green vehicles, and thus reduce carbon emissions through the HOV incentive, the answers to these questions have important implications for policymakers related to the overall effectiveness of the HOV incentive.

In the subsections that follow, we first examine the average effect of the HOV-incentive launch on hybrid-vehicle sales in California and Utah. We then compare the sales effects of the HOV-incentive launch with that of termination. Next, we further investigate the broader implications of the HOV incentive for carbon emissions by examining the relationship of the HOV-incentive termination (and launch) with (1) substitution from or to vehicles with different emission levels, (2) market size, and (3) carpooling behavior.

6.1. The Effect of HOV-Incentive Launch on Unit Sales of Hybrid Vehicles

In this subsection, we estimate the effect of the HOV-incentive launch on unit sales of hybrid vehicles. We follow the same structure we used earlier for the analysis of HOV-incentive termination. Specifically, we replace the $HOVtermination_{it}$ variable in Equation (1) with the $HOVlaunch_{it}$ dummy variable that is equal to one after the HOV incentive is launched if a given county belongs to a state where there is an HOV-incentive launch, and zero otherwise. The fixed effects and control variables are the same as those defined for Equation (1). Also, the interpretation of the coefficient for the $HOVlaunch_{it}$ variable is the same as that discussed for $\beta_{HOVtermination}$ earlier.

Column (1) in Table 4 presents the estimated effect of the HOV-incentive launch on unit sales of hybrid vehicles using a symmetric 12-month window (6 months before and 6 months after) around the HOV-incentive launch. The estimates suggest that the average effect of the HOV-incentive launch on unit sales of green vehicles covered by the incentive is positive (0.016), but statistically insignificant ($p = 0.86$), which amounts to an insignificant 1.61% [exp(0.016) − 1] increase in unit sales in response to the HOV-incentive launch.[32] One might contend that the insignificant effect of the HOV-incentive launch around the close temporal vicinity of the launch could be due to a potential lack of publicity of the incentive at the beginning. If this were the case, the effect of the HOV-incentive launch could become positive and significant over time as more consumers become aware of the incentive. To examine this possibility, we reestimated our main specification by extending the postperiod to 12 months after the HOV-incentive launch. As shown in column (2) in Table 4, the effect of the launch remains insignificant with this longer window. This result is robust to an even wider 18-month postlaunch window.[33] Albeit with a different effect direction, this insignificant main-effect finding gives support to earlier studies that report an insignificant association between the HOV-incentive launch and green vehicle sales (Gallagher and Muehlegger 2011; −7%, $p > 0.10$) and market share (Diamond 2009; −12%; $p > 0.10$).

In addition to our main effect analysis, we also explore the mechanism that underlies the insignificant effect of the HOV-incentive launch on hybrid-vehicle sales. Specifically, we check whether the insignificant effect could be due to an increase in functional value for hybrid vehicles that is offset by a reduction in symbolic value. Similar to the approach we used in our HOV-termination analysis, we add the following interactions to our specification: $HOVlaunch_{it} \times Commute_{it}$ and $HOVlaunch_{it} \times Greenversiononly_j$, along with interactions with other demographics.[34] As shown in column (3) in Table 4, the coefficient for $HOVlaunch_{it} \times Commute_{it}$ is positive (0.058) and significant ($p < 0.01$). This result is in line with an increase in functional value because of time saving.[35] Also, the coefficient for $HOVlaunch_{it} \times Greenversiononly_j$ is negative (−0.412) and significant ($p < 0.001$), providing evidence for a reduction in symbolic value (i.e., signaling greenness).

Besides, similar to our termination analysis, we also add the interaction terms $HOVlaunch_{it} \times MediumSolar_i$ and $HOVlaunch_{it} \times HighSolar_i$ to the specification estimated in column (3) in Table 4. Although the coefficient of the $HOVlaunch_{it} \times MediumSolar_i$ is negative but insignificant (−0.109; $p > 0.1$), the coefficient of the $HOVtermination_{it} \times HighSolar_i$ is negative (−0.523) and significant ($p < 0.05$). This means that unit sales of green vehicles covered by the incentive reduce more in counties with high (versus low) potential for signaling greenness. This result gives further support

Table 4. The Impact of HOV-Incentive Launch on Hybrid Vehicle Sales

Dependent variable: Unit sales	(1) Main effect (6-month post period)	(2) Main effect (12-month post period)	(3) Heterogeneity
HOV incentive launch	0.016	0.063	−1.648**
	(0.183)	(0.085)	(0.611)
HOV incentive launch × Commute			0.058**
			(0.021)
HOV incentive launch × Green version only			−0.412***
			(0.113)
Other interactions	No	No	Yes
Dummies: *Stratum × vehicle model, county, vehicle model × month*	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Number of observations	25,860	54,006	54,006
Log likelihood	−28,861	−63,545	−63,521

Notes. Control variables include vehicle price, state–month-level average gasoline price, county–month-level number of charging stations, and county-level demographic variables that change annually: income, education, age, gender, unemployment rate, and commute. Interactions with other demographics (not reported because of space constraints) include interactions of the incentive termination with the remaining demographics that are part of our control variables.

$^{**}p < 0.01$; $^{***}p < 0.001$.

to a decline in symbolic value following the incentive launch. Combined, these findings are consistent with the view that an increase in functional value after the incentive launch is canceled out by a reduction in symbolic value, resulting in an insignificant launch effect.[36]

6.2. Comparison of the Sales Effects of HOV-Incentive Launch and Termination

The analysis above suggests that, on average, the launch of the HOV incentive results in only an insignificant 1.61% increase in hybrid-vehicle sales. In contrast, the termination of the HOV incentive leads to a decrease of 14.4% in hybrid-vehicle sales. In addition, although the symbolic value of purchasing a green vehicle is found to decrease after the HOV-incentive launch, this reduction is not restored after the incentive termination. In other words, green-vehicle adoption has become partially reliant on the HOV incentive in the long term, because such incentives have crowded out the symbolic motivations to go green. As a result, the effect of incentive termination is not simply the opposite of that of launch, implying that governments' green-product incentives could backfire in terms of boosting the demand for green vehicles.

6.3. HOV Incentive and Greenhouse-Gas Emissions

This subsection studies various factors related to the effectiveness of the HOV incentive in reducing overall carbon emissions.

6.3.1. HOV-Incentive Termination Shifts Consumers to Non-Green Vehicles with High Tailpipe Emissions. An important factor that influences the emission-related implications of the HOV incentive is the potential substitution patterns between hybrid and gasoline vehicles after the incentive ends. To examine such substitution behavior, we estimate a new specification that estimates the heterogeneous (if any) effect of the HOV-incentive termination on unit sales of gasoline vehicles in terms of the tailpipe-emission category of a given vehicle model. We use a categorical (i.e., low, medium, and high) measure for vehicle emissions. The categories are determined based on the terciles of tailpipe emissions of greenhouse gases. To estimate this heterogeneity based on vehicle-emission categories, we add two interactions terms—that is, $HOVtermination_{it} \times MediumEmission_j$ and $HOV\,termination_{it} \times HighEmission_j$—to Equation (1). The estimates reported in column (1) in Table 5 reveal that the HOV-incentive termination shifts consumers to gasoline vehicles with high tailpipe emissions (0.102, $p < .05$).[37]

One possible explanation for this shift is that hybrid vehicles are typically more expensive vehicles relative to gasoline vehicles within a given category. Therefore, it is likely that the second-choice vehicle for consumers who do not purchase hybrid cars in the absence of the HOV incentive is relatively expensive gasoline models, which tend to have higher emissions.[38] To see if this explanation has any support in our data, we include two interaction

Table 5. Heterogeneous Effects of HOV-Incentive Termination by Vehicle Emission Category

Dependent variable: Unit sales	(1) Emission category	(2) Zero-emission
HOV-incentive termination	–0.075	0.081
	(0.093)	(0.192)
HOV-incentive termination × medium emission	0.067	
	(0.069)	
HOV-incentive termination × high emission	0.102*	
	(0.044)	
Other interactions and control variables	Yes	No
Dummies: *Stratum × vehicle model*, *county*, *vehicle model × month*	Yes	Yes
Number of observations	77,713	476
Log likelihood	–94,242	–523

Notes. Column (1) uses the sample of gasoline vehicles and estimates the heterogeneous effect of HOV-incentive termination on unit sales of gasoline vehicles in terms of emission category. Column (2) uses the sample of zero-emission vehicles and estimates the main effect of HOV-incentive termination on unit sales of zero-emission vehicles. Control variables include state–month-level average gasoline price, county–month-level number of charging stations, and county-level demographic variables that change annually: income, education, age, gender, unemployment rate, and commute. Other interactions (not reported because of space constraints) include interactions of the incentive termination with vehicle price and category.

*$p < 0.05$.

terms—that is, $HOVtermination_{it} \times MediumPrice_j$ and $HOVtermination_{it} \times HighPrice_j$—to Equation (1). The price categories are determined based on the terciles. In support of the explanation above, the coefficients of both interactions are positive and significant: 0.128 ($p < .001$) for $HOVtermination_{it} \times MediumPrice_j$, and 0.161 ($p < .001$) for $HOVtermination_{it} \times HighPrice_j$.

We also explore the potential substitution from hybrid vehicles to zero-emission (i.e., electric) vehicles that are not covered by the incentive following the incentive termination. Specifically, we re-estimate our main specification in Equation (1) by using only the sample of electric vehicles. The coefficient for the $HOVtermination_{it}$ dummy is insignificant, as reported in column (2) in Table 5. Therefore, we do not find evidence of demand substitution to electric vehicles after the HOV-incentive termination.[39]

6.3.2. Market Shrinks After the HOV-Incentive Termination. In addition to examining substitution patterns, it is also important to know whether the HOV incentive results in market expansion after its launch and market shrinkage after its termination to assess the overall effectiveness of the HOV incentive in reducing carbon emissions. In columns (1) and (2) of Table 6, we estimate the effects of HOV-incentive termination and launch on total vehicle sales at the county level, respectively. These estimates show that, on average, the new-car market shrinks significantly by 4.7% following the HOV-incentive termination. On the other hand, the new-car market size does not change significantly in response to the HOV-incentive launch.

6.3.3. The Percentage of Carpoolers Increases After the HOV-Incentive Termination. As noted earlier, the HOV incentive was terminated to reduce congestion in HOV lanes, which were originally constructed to encourage carpooling. Thus, it is possible that the HOV-incentive termination could lead to an increase in the percentage of carpoolers in a county because of potentially lower levels of congestion after incentive termination. We check whether this possibility has any empirical support by regressing the annual county-level percentage of carpoolers on the *HOVtermination* dummy along with stratum and year fixed effects. This estimation, reported in column (3) of Table 6, suggests that the percentage of carpoolers significantly increases by 1.9% ($p < .001$) following the HOV-incentive termination. In contrast, as shown in column (4) of Table 6, the percentage of carpoolers does not change significantly after the HOV-incentive launch.

The findings above suggest that there are countervailing forces that influence the overall emission levels. Although the substitution to non-green vehicles with high tailpipe emissions after the HOV-incentive termination implies greater levels of tailpipe emissions, shrinkage in market size for new vehicles and the increase in the percentage of carpoolers imply lower levels of tailpipe emissions. Thus, the direction of the effect of the HOV incentive on overall emissions is mixed. To shed some light on the possible direction of the overall emission effect, we use annual county-level emission data from California around the HOV-incentive termination (such data are not available for California around the HOV-incentive launch and Utah around incentive launch and termination).

Table 6. Market Size and Carpooling Behavior

	Market size		Carpooling	
Dependent variables: Unit sales; percentage of carpoolers	(1) HOV termination	(2) HOV launch	(3) HOV termination	(4) HOV launch (UT)
HOV-incentive change	−0.047*	0.016	0.019***	−0.040
	(0.016)	(0.022)	(0.004)	(0.023)
County dummies	Yes	Yes	No	No
Month dummies	Yes	Yes	No	No
Year dummies	Dropped (because of month dummies)	Dropped (because of month dummies)	Yes	Yes
Stratum dummies	No	No	Yes	Yes
Control variables (see the notes below)	Yes	Yes	No	No
Number of observations	1,879	12,110	274	66
Log likelihood	−5,231	−48,097		
R^2			0.478	0.207

Notes. In columns (1) and (2), we estimate the effects of HOV-incentive termination and launch on total new vehicle sales at the county level using a negative binomial model, respectively. Specifications in columns (1) and (2) contain several control variables, including state–month-level average gasoline price, county–month-level number of charging stations, and county-level demographic variables that change annually: income, education, age, gender, unemployment rate, and commute. In columns (3) and (4), we estimate an ordinary least-squares regression model where the dependent variable is the annual county-level percentage of carpoolers. For the estimation in column (4), we use data from Utah (UT), as carpooling data are not available around the HOV-incentive launch period in California.

$^{*}p < 0.05$; $^{***}p < 0.001$.

We then regress the emission variable on the *HOVtermination* dummy along with county and year fixed effects. We find that the emission is negatively associated with the termination of the HOV incentive. This negative correlation provides some support for the claim that the negative effects of the reduction in market size for new vehicles and the increase in the percentage of carpoolers on emissions can dominate the positive effect of the substitution to non-green vehicles with high tailpipe emissions after the HOV-incentive termination. Combined, our emission-related findings imply that, although the net effect of the HOV incentive on the unit sales covered by the incentive could be negative, the HOV incentive may result in less carbon emission because of market size and carpooling effects. That said, we urge the readers to exercise caution in evaluating the evidence on overall emissions, as the evidence is based on annual data for one state without a control group.

7. Conclusion

In a period when many federal and state governments consider adopting green-vehicle incentives (e.g., Georgia in the United States,[40] Denmark,[41] and New Zealand[42]), it is crucial to understand whether and where these incentives are effective in boosting demand for green products and alleviating the negative environmental externalities of vehicle use. This study empirically examines the effectiveness of a commonly used nonmonetary government incentive—that is, HOV-lane exemption.

The key findings of this study include the following: First, unit sales of vehicles covered by the HOV incentive (i.e., hybrid vehicles) were reduced by 14.4% following the incentive termination. In contrast, on average, green vehicles that are not covered by the HOV incentive (i.e., plug-in hybrid and electric vehicles) and non-green (i.e., gasoline) vehicles did not experience a change in unit sales after the HOV-incentive termination. Second, the HOV-incentive termination had an immediate negative effect right after the announcement of the termination, and it persisted in the medium term (i.e., six months after the incentive termination). Third, in line with the time-saving mechanism, the HOV-incentive termination had a more negative sales effect on vehicles covered by the incentive in counties with longer commute times and those with higher income levels. Fourth, the launch of the HOV incentive resulted only in an insignificant 1.61% increase in hybrid-vehicle sales. Combined with the 14.4% reduction in hybrid-vehicle sales following the HOV-incentive termination, this result suggests that the effect of termination is not simply the opposite of that of launch. Fifth, following the HOV-incentive termination, (1) consumers substituted to non-green vehicles with high tailpipe emissions, (2) the new-car market diminished, and (3) the percentage of carpoolers went up.

7.1 Implications

The findings above have important implications for policymakers and managers. First, given the negative effect of the HOV-incentive termination on green-vehicle sales, policymakers need to consider long-term, adverse consequences of a green-vehicle incentive. The significant decline in hybrid-vehicle sales after the HOV-incentive termination happened more than a decade after the introduction of hybrid vehicles into the market. This implies that green-vehicle adoption has become partially reliant on the incentive, even in the long term.

Second, our finding that the negative impact of the HOV-incentive termination is greater than the insignificant positive impact of the launch implies that nonmonetary incentives such as the HOV incentive can be counterproductive in terms of stimulating demand for green vehicles. The asymmetry in the effects of the HOV-incentive launch and termination appears to stem from the fact that the symbolic value of buying a green vehicle covered by the HOV incentive declines after the launch, but it does not go back up following the termination. Thus, our results reveal an important trade-off policymakers face in deciding whether to provide the HOV incentive: an increase in green-vehicle sales due to increased functional value over the course of the incentive versus a reduction in green-vehicle sales due to reduced symbolic value during and beyond the incentive period.

Third, although the HOV incentive may not be effective overall, our results suggest that it does generate additional sales in markets where consumers have longer commute times and higher income. Such demographic heterogeneity in the effects of the HOV incentive could help local governments choose an appropriate incentive based on the characteristics of the local market under consideration.

Fourth, our findings suggest that policymakers should also consider the impact of the HOV incentive on demand for non-green vehicles, the size of the market, and carpooling behavior while assessing the broader environmental impact of the incentive. Indeed, our findings reveal that the direction of the effect of the HOV incentive on overall emissions is not straightforward. Whereas substitution to non-green vehicles with high tailpipe emissions following the HOV-incentive termination implies greater levels of greenhouse-gas emissions, shrinkage in the market size for new vehicles and the increase in the percentage of carpoolers imply lower levels of emissions. The negative correlation we found between the termination of the HOV incentive and total emission levels in California implies that the adverse impact of the incentive termination on green-vehicle sales might have had an unintended positive consequence in terms of gas emissions. This, in turn, provides support to a common, but untested, criticism that the HOV incentive runs counter to other policies designed to promote energy-efficient practices.

Fifth, companies increasingly engage in green-branding activities to attract new customers, including those that value signaling a green image through their green-product purchases. Our findings supporting a negative net effect of the HOV incentive on green-vehicle sales imply that firms' ability to sell their products based on the "green image" could be undermined by counterproductive government policies. In particular, government incentives for green products can reduce the symbolic value consumers derive from green products, and, thus, they can have a direct harmful impact on the effectiveness of companies' green-branding efforts. Also, our results regarding the heterogeneity of the effectiveness of the HOV incentive in terms of time (i.e., short versus medium term), as well as local market characteristics (i.e., commute times and income), could help managers tailor their production schedules and inventory levels in response to government incentives.

Finally, managers need to take into account the impact of government incentives on the demand for non-green products along with their effect on green products. Our finding that the new-car market shrinks after the termination of the HOV incentive suggests that some consumers may not simply switch to other vehicle options. Instead, they may prefer carpooling, as revealed by our analyses. Furthermore, our results indicate that some manufacturers could be less vulnerable than others to the impact of governments' green-product incentives on their non-green vehicle sales. Because we show that the HOV-incentive termination shifts consumers to non-green vehicles with high emissions, manufacturers with a larger portfolio of such vehicles could be less negatively affected after the termination of the HOV incentive. This points to another strategic consideration for companies that invest in their green-vehicle portfolio.

7.2. Limitations and Future Research

Although we provide an extensive set of robustness checks, including alternative identification strategies, readers should assess the evidence as they would in any study relying on observational data. In this study, we examine the sales effect of HOV-incentive terminations for conventional hybrid vehicles in a context where a future HOV incentive was expected for newer models of green vehicles. Although we have provided several types of evidence to allay the concerns associated with this feature of our setting, readers should be cautious in extrapolating our findings to contexts without pending incentives. More research on the effectiveness of other types of monetary and nonmonetary incentives would enhance our understanding of which incentives work best to promote green products and why. Furthermore, our analyses in this paper concentrate on incentive changes in two states. It is important to note that these states are part of different regions based on the Bureau of Economic Analysis. Although California is part of Far West, Utah belongs to Rocky Mountain. As such, our results can be generalizable to two different regions. Also, our findings related to the impact of the HOV-incentive launch are in line with prior studies using data from other states. We hope that future studies will shed further light on the generalizability of our results, as more states launch and terminate their HOV incentives. Finally, a more comprehensive structural analysis of the welfare implications of green-product incentives is another fruitful direction for future research.

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Endnotes

[1] See https://en.oxforddictionaries.com/definition/green_technology. Other terms used for green products include "eco-friendly," "sustainable," "clean," and "environmentally friendly" (e.g., Sheldon and DeShazo 2017).

[2] See https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions.

[3] See https://afdc.energy.gov.

[4] HOV lanes are also referred to as express lanes, carpool lanes, transit lanes, diamond lanes, or commuter lanes. There are two types of hybrid vehicles in the automobile market in our study period: conventional hybrid and plug-in hybrid. Both types of vehicles have an electric motor and a rechargeable battery. Although conventional hybrid vehicles can only be fueled by gasoline, plug-in hybrid vehicles can be plugged in and recharged from an outlet. In the remainder of the paper, we use "hybrid vehicle" to refer to conventional hybrid vehicles and "plug-in hybrid vehicle" to refer to plug-in hybrid vehicles.

[5] See https://afdc.energy.gov.

[6] See http://www.nytimes.com/2007/07/04/business/04hybrid.html.

[7] There is a related, but separate, marketing literature that examines the role of social effects in the adoption of green technology. Bollinger and Gillingham (2012) investigate the role of social effects in the diffusion of solar photovoltaic panels in California. Narayanan and Nair (2013) propose solutions to identify installed-base effects, and they apply these approaches to the case of Toyota Prius electric-car adoption in California.

[8] The author finds a positive association between the HOV-incentive launch and hybrid-car market share only in Virginia.

[9] Note that there were only a few plug-in hybrid and electric-vehicle models available in our analysis period. Additionally, the insignificant average sales effect for vehicles that are not covered by the HOV incentive does not necessarily mean that there is no substitution between vehicles that are covered by the HOV incentive and those that are not. We explore this issue in our subsequent analyses.

[10] See http://articles.latimes.com/2004/apr/09/local/me-hybrid9.

[11] See http://articles.latimes.com/2004/apr/14/opinion/oe-poole14.

[12] See http://articles.latimes.com/2011/jul/02/local/la-me-07-02-carpool-lanes-20110702.

[13] See http://articles.latimes.com/2007/sep/12/local/me-carpool12.

[14] See http://articles.latimes.com/2009/sep/28/business/fi-hybrid-stickers28.

[15] We discuss the potential implications of this feature of our context in the subsequent sections. Electric cars would continue to retain their HOV-lane privileges around the HOV-incentive terminations we study.

[16] See http://archive.sltrib.com/article.php?id=58094075&itype=cmsid.

[17] The list of green vehicles available during our observation period is provided in Online Appendix A.

[18] See The specific criteria are shown in Table B.1 in Online Appendix B.

[19] See https://www.census.gov/programs-surveys/acs.

[20] See https://guides.library.harvard.edu/hks/campaigns_elections.

[21] See https://democrats.org/where-we-stand/the-issues/environment/.

[22] See https://www.eia.gov/dnav/pet/pet_pri_gnd_dcus_nus_w.htm.

[23] The details of these two groups are provided in Subsection 4.1.

[24] Only five counties out of 27 counties are discarded after matching for the HOV-incentive termination analysis. Our results remain similar when we estimate DiD using all counties (i.e., without dropping counties because of matching), as shown in Table D.1 in Online Appendix D.

[25] Our conclusions do not change when we combine data across the three vehicle types and estimate a specification where we interact the incentive change with vehicle type.

[26] One concern with any study of the regulation of incentives is that the dates of enactment might not give precise measurement of the incentive's effect because of the anticipation or awareness of the target population. Therefore, in our main specification, we use the DMV's announcement about the HOV-incentive termination to define the treatment start date. In Subsection 4.3, we show robustness to an alternative treatment start date—that is, the actual month of incentive termination.

[27] We provide various specifications with different subsets of fixed effects as well as with and without controls in Table E.1 in Online Appendix E. The consistently negative and significant coefficients for the HOV-incentive termination dummy suggest that the effect of any remaining unobservables would need to be relatively large compared with the factors we account for to result in a significant change in our qualitative results (Altonji et al. 2005).

[28] We have also estimated similar interaction specifications using HOV-lane miles (which was used by previous studies, such as Sheldon and DeShazo 2017) or the distance between the centroid of a county and the closest HOV-lane point to that centroid, instead of commute time. The estimates indicate that the drop in unit sales for the green vehicles covered by the incentive following the HOV-incentive termination is greater in counties with (1) more HOV-lane miles and (2) shorter distance to HOV lanes. However, as a large majority of variation (around 85%) in these two measures of HOV access is captured by the $HOVtermination_{it} \times Commute_{it}$ as well as other fixed effects and control variables, the interactions of these two measures with the HOV-termination dummy become insignificant when we also include $HOVtermination_{it} \times Commute_{it}$. Therefore, we only report the coefficient for the $HOVtermination_{it} \times Commute_{it}$ interaction in Table 3.

[29] The highest correlation across demographic variables is between income and education, which is equal to 0.604. All other correlations have an absolute value smaller than 0.5.

[30] We thank an anonymous reviewer for bringing this possibility to our attention.

[31] We also consider other ways to address this alternative explanation in Online Appendix H.

[32] We provide various specifications with different subsets of fixed effects, as well as with and without controls in Table I.1 in Online Appendix I. The consistently insignificant coefficients for the HOV-incentive launch dummy suggest that the effect of any remaining unobservables would need to be relatively large compared with the factors we account for to result in a significant change in our qualitative results (Altonji et al. 2005). Additionally, in various online appendices, we show that our incentive launch findings are robust to (1) different functional forms (Table I.2), (2) different treatment states (Table I.3), and (3) differential trends across strata (Table I.4).

[33] We also examined the web-search interest (based on Google Trends) in specific search terms related to the HOV-incentive launch in California, including "yellow sticker," "yellow decal," "HOV hybrid," and "carpool hybrid." The trend in the interest for these terms suggested that the interest in the HOV incentive was highest right after the actual launch of the incentive, and it diminished over time. Therefore, the 18-month post-launch window we used in our HOV launch analysis covers a longer period than the period when the interest was at its peak.

[34] Note that we do not include the $HOVlaunch_{it} \times Income_{it}$ interaction, because, in our data for the HOV launch analysis, there is not adequate variation in $HOVlaunch \times Income_{it}$ to exploit after incorporating $HOVlaunch_{it} \times Commute_{it}$ as well as other interactions, fixed effects, and control variables. When we exclude the $HOVlaunch_{it} \times Commute_{it}$ interaction, the coefficient for the $HOVlaunch_{it} \times Income_{it}$ interaction becomes positive and significant.

[35] This finding is in line with anecdotal evidence suggesting that the HOV incentive has helped to sell hybrid vehicles, especially if such a perk is a deal-breaker (https://www.wsj.com/articles/SB100014240527023038121045764417811904000 52).

[36] We also consider an alternative explanation related to the pending availability of greener electric-vehicle models in Online Appendix J, but we do not find support for this explanation.

[37] We also estimated a similar heterogeneity specification for the HOV-incentive launch. The interactions of vehicle-emission categories with the HOV-incentive launch were insignificant, which is in line with the fact that the HOV-incentive launch does not have a significant main effect on hybrid-vehicle sales.

[38] We thank an anonymous reviewer for this insight.

[39] Note that demand substitution from electric vehicles following the HOV-incentive launch was not possible, because electric vehicles were not available around the incentive launches.

[40] See https://politics.myajc.com/news/state--regional-govt--politics/georgia-lawmakers-try-bring-back-electric-vehicle-tax-break/MJIY2sPBwYK4NXAtHsEqRJ/.

[41] See https://cleantechnica.com/2018/05/01/denmark-rethinks-ev-incentives-after-market-collapses/.

[42] See https://www.newshub.co.nz/home/politics/2018/09/government-promises-decent-incentives-for-electric-cars.html.

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