# Hybrid Vehicles, Social Signals and Household Driving: Implications for Miles Traveled and Gasoline Consumption


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**Abstract**

We estimate the effect of gasoline-electric hybrid vehicle ownership on household annual miles traveled. We focus on two types of rebound effects associated with hybrid adoption. The first is a social status driven rebound effect arising out of the signaling value associated with visually distinct hybrid vehicles. The second is the total rebound effect: in addition to any social status effects, the higher fuel efficiency of gasoline-electric vehicles leads to a lower cost per mile. We recover causal effects using a matching strategy to account for observable and unobservable factors that influence both hybrid adoption and miles traveled. While we do not find evidence of a significant social status rebound effect, we estimate an overall hybrid rebound of about 3 percent of the (average) annual miles traveled. This rebound effect is not sufficient to offset the reduction in fuel consumption associated with the higher fuel efficiency of the hybrid and we find that hybrid adoption reduces fuel consumption by 34 to 46 percent per year compared to conventional gasoline powered vehicles.



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## 1 Introduction

The United States government has spent millions of dollars since 2006 encouraging households to purchase fuel efficient vehicles, largely in response to oil price shocks and rising greenhouse gas emissions from fossil fuel dependent transportation (US EPA 2015). Over the 2000's decade gasoline-electric hybrid vehicles such as the Toyota Prius and Honda Civic hybrid became nearly synonymous with high fuel efficiency. The Energy Policy Act of 2005 provided a substantial income tax credit for the purchase of gasoline-electric hybrids; Sallee (2011) calculates that the 2007 third quarter cost of these incentives was nearly 800 million dollars. More recently, the Energy Improvement and Extension Act of 2008 provides similar tax credit incentives for plug-in electric vehicles, continuing the policy focus on alternative-fuel vehicles.[2] The goal of these policies is to reduce gasoline consumption and corresponding greenhouse gas emissions by stimulating the adoption of more fuel-efficient vehicles. Understanding the relationship between hybrid ownership and gasoline consumption is not only important for evaluating the effectiveness of policies directed toward hybrid adoption, but also for predicting the possible effects of subsequent policies focusing on other alternative-fuel vehicles.

The higher fuel efficiency of gasoline-electric hybrids lowers the cost of travel and is expected to increase vehicle miles traveled (Chan and Gillingham 2015). Our objective is to estimate this rebound effect or the extent to which the adoption of a hybrid vehicle increases household annual miles traveled and thus offsets the reduction in fuel consumption due to the higher fuel efficiency of the hybrid.

A natural question is whether hybrid vehicles are substantially different from relatively fuel-efficient conventional engine vehicles, and therefore whether a hybrid vehicle rebound effect is worth investigating. We believe it is, for two reasons. First, we postulate that there is a social status driven rebound effect that is specific to visually distinct hybrid vehicles. Over the 2000s decade, which is also our sample period, the Toyota Prius was the only visually distinct gasoline-electric hybrid vehicle on the market, and became synonymous

[2] More information on the Plug-In Electric Drive Vehicle Credit can be found at http://www.irs.gov/Businesses/Plug-In-Electric-Vehicle-Credit-IRC-30-and-IRC-30D (accessed September 14, 2017).

with the term "hybrid."[3] Recent work (e.g., Narayanan and Nair 2013, Sexton and Sexton 2014, Delgado et al. 2015) documents that this visual distinctiveness of the Prius provides a signal that its driver adheres to (local) biocentric social norms, and that this environmental social status signal is an important and statistically significant factor explaining the proliferation of the Toyota Prius.[4] While every vehicle has a unique trim, the perception of the Prius as a gasoline-electric vehicle with a lower environmental footprint is singular. We propose, then, that the owner of a visually distinct hybrid has an incentive to drive more to better send out the social status signal. We are the first to empirically estimate this social status driven rebound effect and the extent to which the visual distinctiveness of the Toyota Prius might negate the potential gains from the higher fuel-efficiency.[5]

The second contribution of this paper is to estimate the overall rebound effect associated with ownership of any hybrid vehicle. This rebound effect comprises the "traditional" rebound effect that stems from the increased fuel-efficiency of the hybrids as well as the rebound effect due to social status signaling. Because households self-select into hybrid vehicle ownership, it begs the question whether the behavior of these households is different from the behavior of households that own relatively fuel efficient vehicles with conventional gasoline powered engines.

To measure the social status driven rebound effect, we model ownership of the Toyota Prius, the only visually distinct hybrid in our dataset, as treatment, and compare annual miles traveled between Prius-owning households and their non-Prius hybrid-owning counterparts. To measure the total rebound effect, we consider hybrid ownership as a treatment and estimate the treatment effect as the difference in annual miles traveled by hybrid household and their non-hybrid (conventional engine) counterparts. As our

[3] Indeed, the Prius was specifically designed by Toyota to be visually distinct from all other vehicles on the road (Sexton and Sexton 2014), which contributed to the widespread popularity of the Prius over the 2000s decade.

[4] By biocentric social norms, we refer to the degree to which there are social incentives for individuals to show concern for the natural environment. There is precedence in the literature indicating that these social incentives can be a significant source of motivation underlying individual consumer behavior, and that these social norms may be spatially heterogeneous (e.g., Kahn 2007, Sexton and Sexton 2014).

[5] The social status rebound effect is driven by a behavioral response and is beyond the scope of a standard theoretical treatment of the rebound effect, but it is not inconsistent with microeconomic theory on consumer behavior in the presence of interdependent utility. Chan and Gillingham (2015) reference the possibility of a status-driven behavioral response to increased energy efficiency (see page 141), but do not pursue the theory further given their focus on what we call the total rebound effect.

objective is to explore the (causal) realized impact of hybrid ownership on vehicle miles traveled as a lens for gauging the effectiveness of recent policies, for both treatments we focus on the average treatment effect on treated households. We combine these treatment effect estimates with the higher fuel efficiency of hybrids relative to conventional engine vehicles to calculate the average reduction in fuel consumption from hybrid adoption.

Our empirical strategy centers on a matching approach, that allows us to impute the counterfactual annual miles traveled for hybrid-owning (Prius-owning) households from a subset of non-hybrid-owning (non-Prius-owning) households that are identical in important dimensions. Many of these dimensions are observable. For instance, a household that commutes a great distance to work will travel a greater number of miles per year, and will also be more likely to adopt a hybrid in order to offset some of the costs of travel. The matching approach is a flexible means of eliminating covariate imbalance with regards to such observable factors that may ultimately be a source of bias. In addition, local social norms, household preference for lower travel cost (i.e., beyond observable correlates such as commute distance or income), and household preference for environmental preservation may also correlate with both hybrid adoption and annual miles traveled, but is difficult to observe. To eliminate the possibility of bias due to these factors, we further require an exact geographical match between treated and untreated households at the CBSA or zip code level, and a nearest-neighbor match on the average fuel efficiency of other vehicles in the household (that do not define treatment). These additional matching restrictions ensure that each matched household pair faces identical local social norms and also has the same general preferences for lower travel cost and environmental preservation. We elaborate on the details and underlying assumptions of our matching strategy in Section 4.

The majority of our data come from the 2009 National Household Travel Survey (NHTS). Our final estimation sample includes 36,780 households, of which 1,285 own at least one gasoline-electric hybrid of any type, and 696 own at least one Toyota Prius. In total, we have 85,940 vehicles of which 1,356 are hybrid vehicles and 726 of these hybrids are Toyota Priuses. Our use of household level data to investigate vehicle rebound effects, though not unique, is a departure from the majority of studies that measure automobile rebound effects (for conventional engine vehicles) at an aggregate level (e.g., Greene 2012). Further, the richness of our data – both in terms of the large pool of potential control households and the scope of the available variables – facilitates our use of matching. Pre- and post-match balance assessments indicate that the set of matched households is free from nearly all potential sources of bias for the hybrid treatment model, and the potential for bias is relatively small for the model of Prius treatment.

We find no evidence of a statistically significant social status driven rebound effect. That is, while a visually distinct hybrid bears value as a signal of environmental social status that is capitalized in its market price (e.g., Delgado et al 2015), this visual distinctiveness does not induce an extra rebound effect. We do find that, overall, hybrid adoption causes an average household to drive more miles per year compared to a non-hybrid counterfactual household. This total rebound effect is only about 3 percent of the household annual miles traveled, and is insufficient to offset the reduction in fuel consumption coming from the higher fuel efficiency of the gasoline-electric hybrid engine. We estimate that hybrid vehicle adoption generates a substantial reduction in fuel consumption, on the order of 34-46 percent per year.

## 2 Discussion of Related Research

### 2.1 Factors that Influence Hybrid Adoption

Several socio-economic factors that correlate with hybrid vehicle adoption, such as income, education, or age are commonly accounted for in the literature (Ozaki and Sevastyanova 2011, Heutel and Muehlegger 2014). Our discussion here focuses on more complex incentives.

**Gasoline Price and Fuel Efficiency** Gasoline prices rose for much of the 2000s decade. This rise is partly responsible for the increasing market share of the relatively fuel efficient gasoline-electric hybrid vehicles (Diamond 2009, Beresteanu and Li 2011, Ozaki and Sevastyanova 2011). Heffner et al. (2005) and Klein (2007) find that higher gas mileage is a significant factor underlying hybrid adoption.

**Personal Preference for Environmental Quality** There is a growing consensus that consumers value environmental quality for reasons not limited to altruism, egoism, guilt, or off-setting; see, for example, Kotchen (2005, 2006, 2009). Heffner et al. (2005), Kahn (2007), and Ozaki and Sevastyanova (2011) find that the environmentally friendly image of a hybrid and the desire to reduce pollution are important motives for consumers who purchase a hybrid. These preferences are difficult to observe or disentangle (Delgado et al. 2015), motivating some authors to use proxy variables to account for these preferences (Kahn 2007, Gallagher and Muehlegger 2011, Heutel and Muehlegger 2014).

**Openness to New Technology** The gasoline-electric hybrid is a symbol of new automobile technology. Turrentine and Kurani (2007) and Ozaki and Sevastyanova (2011) find that consumers adopt hybrid vehicles because they enjoy pioneering new technology.

**Hybrid Vehicle Diffusion** Mau et al. (2008) and Axsen et al. (2009) find that market penetration influences consumers' preference or willingness to pay for hybrid vehicles. Narayanan and Nair (2013) find a positive and significant effect of past hybrid vehicle adoption on current hybrid vehicle adoption for the Toyota Prius. Heutel and Muehlegger (2014) study the impact of a cumulative hybrid vehicle penetration rate for the Toyota Prius and Honda Insight on hybrid vehicle sales, and find a positive impact for the Prius and a negative impact for the Insight. Evidence indicates that as hybrid vehicles, especially the Toyota Prius, become more commonplace, consumers are more likely to purchase a hybrid.

**Social Norms** Hybrid owners earn positive social status in an environment in which social norms value environmental amenities. Ozaki and Sevastyanova (2011) find that social orientation, the willingness to comply with social norms, and peer effects are important factors motivating purchase of a Toyota Prius in the United Kingdom, and Kahn (2007) finds that people living in a more environmentally friendly community are more likely to adopt a hybrid. There is compelling evidence that consumers use hybrid vehicles (particularly the Toyota Prius) as a tool to signal their social awareness, responsibility, and concern for others (Heffner et al. 2005, 2007, Axsen et al. 2009, Sexton and Sexton 2014, Delgado et al. 2015).

**Government Sponsored Financial Incentives** The federal government and some state governments have spent large sums of money encouraging households to invest in hybrid vehicles.[6] Chandra et al. (2010), Beresteanu and Li (2011), Gallagher and Muehlegger (2011) and Ozaki and Sevastyanova (2011) find that government incentives (such as tax incentives or traffic policies) significantly increase hybrid adoption, though the impact may be smaller than that of a modest increase in gasoline prices (Beresteanu and Li 2011) or may vary by type and size of the incentive (Gallagher and Muehlegger 2011). Conversely, Diamond (2009) does not find that financial policy incentives impact hybrid adoption. Identifying the effect of these incentives is difficult because these incentives may be collinear with time trends, are common to many households, and because the effects may be confounded by consumer self-selection into the hybrid market (Chandra et al. 2010).

## 2.2 Factors that Influence Household Driving Habits

**Residential Location** A large number of previous studies have found that the population density and the level of urbanization in a household's residential location are important factors influencing miles traveled (Cervero 1996, Stead 2001, Holtzclaw et al. 2002, Schwanen and Mokhtarian 2005, Ewing et al. 2007, Brownstone and Golob 2009, Cervero and Murakami 2010).

**Socioeconomic Characteristics** There is strong empirical evidence that miles traveled are affected by household socioeconomic characteristics, such as income, size, household vehicle ownership, gender, age, and the working status of household members (Stead 2001, Holtzclaw et al. 2002, Johansson-Stenman 2002, Brownstone and Golob 2009). Generally, households with a higher income, more members, or more workers drive more; males drive more than females; middle-aged drivers drive more than older and younger drivers. It is important to control for these household characteristics when estimating the effect of hybrid/Prius adoption on household miles traveled.

## 2.3 Empirical Estimates of the Rebound Effect

[6] Borenstein and Davis (2015) review a variety of federal government incentives designed to encourage environmentally friendly behavior in a variety of ways, one of which is hybrid vehicle adoption.

The automobile rebound effect literature focuses on improvements in fuel efficiency for conventional engine vehicles, not for hybrid vehicles specifically. To date, none have considered the possibility of a social status driven rebound effect. Some of the earlier studies use aggregated (i.e., state level) data and estimate rebound effects ranging from 5 percent to 31 percent in terms of miles traveled (Greene 1992, Jones 1993, Haughton and Sarkar 1996). Others use disaggregated (i.e., household level) data and find substantially varying rebound effects. Goldberg (1998) and Greene et al. (1999) estimate the rebound effect to be 20 percent and 23 percent, respectively; the lowest rebound effect is found by Pickrell and Schimek (1999) to be 4 percent; the highest is found by West (2004) to be 87 percent.

More recently, Small and Van Dender (2007) measure the rebound effect from an increase in fuel efficiency on travel distance at the state level in the United States. They estimate short term rebound effects of 4.5 percent (1966-2001) and 2.2 percent (1997-2001), and long term rebound effects of 22.2 percent (1966-2001) and 10.7 percent (1997-2001). Hymel et al. (2010) extend the research period to 1966-2004 and find the rebound effects are 4.7 percent and 24.1 percent in the short term and long term, respectively. Using Canadian data, Barla et al. (2009) estimate a short term rebound effect of 8 percent and a long term rebound effect of 20 percent. Wang et al. (2012) estimate the rebound effect to be as high as 96 percent in urban China.

However, one caveat to these studies is that they measure the rebound effect by calculating the elasticity of travel distance to a change in fuel cost (per mile), not in fuel efficiency specifically. The assumption behind this method is that consumers respond equally to an improvement in fuel efficiency and to a decrease in fuel price. However, there is evidence that consumers are usually more responsive to a decrease in fuel price (Gillingham 2011). Similarly, Greene (2012) and De Borger et al. (2016) reject the null hypothesis that the elasticities of vehicle travel with respect to fuel prices and fuel efficiency are equal with opposite signs, and find consumers’ response to fuel efficiency is much smaller than their response to fuel price. Therefore, a rebound effect of fuel efficiency measured by the elasticity of travel distance with regard to fuel cost may be overestimated.

Greene (2012) and De Borger et al. (2016) separate the effect of fuel efficiency from the effect of fuel price, and are the closest to our study in terms of the estimation of the rebound effect. Compared to these and other previous studies, our study makes two contributions. First, we focus on two rebound effects associated with hybrid vehicles: the social status rebound effect and the total rebound effect. Second, previous authors use traditional regression methods whereas we use a covariate matching method to directly compare the driving distances of households that are identical to each other in all respects except whether the vehicles they drive are hybrids/Prius. The first advantage of our matching approach is that we do not rely on the regression functional form for extrapolation of the counterfactual; Imbens and Rubin (2015) also describe how regression estimates of causal parameters can be sensitive to imbalance in the covariates, which, as we show in Appendix A, exists in our unmatched sample. The second advantage of our matching approach is that by requiring an exact match on certain discrete variables, we are able to eliminate the influence of certain unobservable factors on our estimates. Finally, by requiring matched households to face the same fuel price, we separate the effect of fuel efficiency from the fuel price effect.

de Haan et al. (2006) and de Haan et al. (2007) are the only two studies that focus on hybrid vehicle rebound effects, though they do not investigate whether Prius buyers drive more than non-hybrid owners. Instead, using a sample of Toyota Prius buyers in Switzerland, they investigate whether households switch to the Prius from a smaller vehicle, and whether vehicle ownership might increase. They do not find evidence that either of these two rebound effects is significant.

# 3 Model, Identification, and Estimation

## 3.1 Empirical Propositions

**Proposition 1** *There exists a social status driven rebound effect associated with visually distinct hybrid vehicles.*

We postulate that a household that owns a visually distinct hybrid vehicle has an incentive to increase its driving in order to fully capture the social status benefits afforded by the visual distinctiveness of the hybrid. Our strategy to estimate the social status rebound effect is based on special visual characteristics of the Toyota Prius. While most hybrid vehicles can only be identified from their non-hybrid counterparts by the hybrid label on the rear of the car, the Toyota Prius was designed to be visually distinct from all other vehicles, and is instantly recognizable. Sexton and Sexton (2014) and Delgado et al. (2015) find that households are willing to pay for this symbolic benefit of the Toyota Prius in order to signal their environmental status. In our dataset, the Prius is the only visually distinct hybrid, so if there is a social status rebound effect, we expect to find that a household that owns a Prius drives more than a household that owns a non-Prius hybrid. Therefore, to assess this empirical proposition we restrict the sample to only hybrid households and define Prius ownership as treatment to estimate the social status rebound effect.

**Proposition 2** *Ownership of a gasoline-electric hybrid vehicle leads to an increase in annual household vehicle miles traveled.*

In line with Chan and Gillingham (2015), we expect that a household responds to the ownership of a hybrid by increasing annual travel distance, and that this effect is due to the improved fuel efficiency of hybrids compared to similar conventional engine vehicles and the potential for certain hybrids to signal environmental preferences. To assess this empirical proposition, we use our full sample of households, taking all households that own a hybrid of any kind as our treated group.

## 3.2 Empirical Framework

### 3.2.1 Econometric Model

We imagine two potential outcomes:

$$\begin{aligned} Y_{1i} &= \mu_1(X_i) + U_{1i} \\ Y_{0i} &= \mu_0(X_i) + U_{0i} \end{aligned} \tag{1}$$

in which $Y_{ji}$ is the total annual vehicle miles traveled by household $i = 1, 2, \ldots, n$ in vehicle state $j = 0, 1$ for which $j = 1$ denotes receipt of treatment and $j = 0$ denotes no treatment, $X_i$ is a $k$-dimensioned vector of observable household-specific factors that influence driving distance, $\mu_j(X_i)$: $\mathbb{R}^k \to \mathbb{R}$ is the conditional mean of $Y_{ji}$ given $X_i$, and $U_{ji}$ is an error term that captures unobservable factors that influence miles traveled. This model describes two possible treatment states from which the household chooses – treated or untreated – and allows the household to select into a state based on both observable and unobservable factors.

We define the two treatments, Prius treatment and hybrid treatment, as whether or not a household owns a Prius or a hybrid, respectively. Specifically, for Prius treatment, any household that owns at least one Prius that was purchased brand new by the household is included in our treated group, and any household that owns a non-Prius hybrid that was purchased brand new is part of the control group. Likewise for hybrid treatment: any household that owns at least one hybrid (of any kind) that was purchased brand new is included in the treatment group, and any household that does not own any hybrid vehicle but has purchased at least one brand new non-hybrid vehicle is part of the control group.[7] We limit all purchases, including hybrid purchases and non-hybrid purchases, to be after 2000 to avoid systematic bias because hybrid purchases only appear after 2000 in our sample.

Define $\Delta_i = Y_{1i} - Y_{0i}$ to be the effect on miles traveled from driving a hybrid (Prius) – the treatment effect for household $i$. We estimate the average effect of treatment on treated households ($\tau_{att}$),

$$\tau_{att} = E[Y_{1i}|X_i, H_i = 1] - E[Y_{0i}|X_i, H_i = 1] \quad (2)$$

where $H_i$ is a binary indicator for whether or not the household owns a hybrid (Prius). We focus on this parameter because we are interested in understanding the extent to which hybrid adoption to date has reduced fuel consumption. In addition, identification of the average effect of treatment on any randomly selected household requires a full support condition of the propensity score (e.g., Heckman et al. 1998), but this condition fails in our data. Rather, our data supports identification of the average effect of treatment on the treated population.[8]

[7] We limit the vehicle purchases to be brand new vehicle purchases because only brand new hybrids qualify for the government-sponsored policy incentives for hybrid adoption, which is an important factor influencing households' adoption decisions of hybrids. To determine whether a purchased vehicle is brand new or used, we follow the criterion used by NHTS: when the difference between the purchase year and the model year of a vehicle is less than two years, we assume the vehicle is purchased brand new; otherwise, we assume the vehicle is purchased used.

[8] Our probit estimates of the propensity score (reported in the unpublished Supplemental Appendix) show the range of support being (0.000, 0.458) for the hybrid ownership model and (0.000, 0.953) for the Prius ownership model. Across probit models we estimate we do not obtain estimates of the propensity score for the hybrid model that have a maximum support that exceeds 0.55, which means that comparison of

We can directly estimate $E[Y_{1i}|X_i, H_i = 1]$ using observational data, but not the counterfactual $E[Y_{0i}|X_i, H_i = 1]$. The typical way to deal with this problem is to approximate $E[Y_{0i}|X_i, H_i = 1]$ using a control group of non-hybrid-owning households. We use a matching method to impute the counterfactual outcome for hybrid drivers nonparametrically via $\hat{Y}_{0i} = \frac{1}{M}\sum_{m=1}^{M} Y_m$ for the $M$ closest matches to household $i$ in terms of observable characteristics. We conduct exact matching and nearest-neighbor matching based on the Mahalanobis distance metric $A = (X_i - X_{i'})' S^{-1} (X_i - X_{i'})$ where $S$ is the sample covariance between household $i$ and matched households. Each hybrid-owning household can be matched to one or more non-hybrid-owning households, depending on the value of $M$. Imbens (2004) indicates that one-to-one matching is the approach with the least bias, so we use $M = 1$.

Specifically, we match each household that has purchased a brand new hybrid (Prius) vehicle to a similar household that has purchased a brand new non-hybrid vehicle (non-Prius hybrid). The ideal match consists of household pairs that are the same in all dimensions with the only difference being whether or not the brand new vehicle purchased is a hybrid (Prius). Since the purchased brand new vehicle in each household plays an important role, our selection rule is as follows. For non-hybrid (non-Prius) households, we focus on the most recent purchase because that purchase represents the most recent opportunity for the household to receive treatment (but did not). For hybrid (Prius) households, we choose the purchase of a brand new hybrid (Prius); if a household purchased more than one hybrid (Prius) then we choose the first hybrid (Prius) purchase since that purchase is the one for which the household became a treated household.

The reliability of the matching method to approximate the counterfactual for treated households depends on whether all factors that affect both hybrid (Prius) adoption and driving behavior can be balanced via the match. We use pre- and post-match balancing metrics to assess the potential for bias in our estimates.

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households on the basis of observable demographics does not have sufficient power to satisfy the full support condition. In all models, we find estimates of the propensity score arbitrarily close to zero, which indicates that the $ATT$ is identified but ATE is not. These results are intuitive. It is easy to find non-hybrid households that match the same demographic characteristics of hybrid households.

### 3.2.2 Identification

We are primarily concerned with three unobservable factors: household preferences for lower travel cost, household preferences for environmental quality, and the local social norms each household faces. A household that has stronger preference for lower travel cost and environmental quality is more likely to purchase a hybrid (Prius) vehicle, and also tends to drive less. A household that lives in an area with stronger social norms for environmental protection has greater incentive to purchase a hybrid (Prius), but may also have greater incentive to drive the hybrid (Prius) more to send out a signal that he/she conforms to these social norms. To control for these three unobservable factors in our model, we use the average fuel efficiency rating of all other vehicles (excluding the vehicle defining the treatment status of the household) owned by each household, to approximate unobservable preferences for lower travel cost and environmental quality, and control for local social norms via exact matching on a categorical geographic indicator.

Specifically, our identification strategy is based on the following assumptions:

*(i) Ceteris paribus, unobservable household preference for lower travel cost and environmental preservation is positively related to the fuel efficiency ratings of all vehicles in the household.*

A household with stronger preference for lower travel cost and/or environmental preservation will *ceteris paribus* choose more fuel efficient vehicles, so we expect that such households will have a higher average fuel efficiency rating across all vehicles. This allows us to control for the effects of the unobservable preferences on both hybrid adoption and vehicle miles traveled by matching households on the average fuel efficiency rating of vehicles owned by each household. As we mentioned, one vehicle in each household has been selected to define the treatment status of the household. To ensure that this vehicle does not influence the measure of household preference on lower travel cost and environmental preservation when it already defines the treatment status of the household, we exclude this vehicle from the calculation of household vehicle fuel efficiency. Hence, household vehicle fuel efficiency is measured by the average miles per gallon (MPG) of vehicles in each household other than the vehicle defining the treatment status of the household (we refer to this as MPG of other vehicles). As a result, we restrict our data to a sample of households that own multiple vehicles.

The idea of using this MPG rating as an indicator for household environmentalism is new, but the idea of controlling for environmentalism via proxy variables is not. Kahn (2007) uses a community's share of Green Party registered voters as a proxy for community environmentalism and finds that households living in communities with greater Green Party support are more likely to purchase more fuel efficient vehicles. Gallagher and Muehlegger (2011) use Sierra Club membership, and Heutel and Muehlegger (2014) use League of Conservation Voters scores, as measures of preference for environmentalism. Our proxy measure of household environmental preference has the advantage of being uniquely determined for each household in our sample rather than being determined by broader community characteristics common to multiple households.

*(ii) Households living within the same geographic area are subject to the same local social norms.*

Previous research has shown that households living in the same geographic area face similar social norms with respect to vehicle ownership and use (Kahn 2007, Sexton and Sexton 2014). By matching households in the same geographical area, we are able to eliminate the effect of local social norms. We consider two strategies for restricting matched households to reside within the same geographical area: the first requires that matched households reside in the same CBSA, and the second requires matched households to reside in the same zip code area. Matching households at the zip code level allows us to relax the assumption of homogeneity of social norms within each CBSA. We realize that this assumption rules out the effects of complex networks, such as differences in social incentives faced by households at home versus at work or heterogeneity in network connections within a particular neighborhood. However, these complexities are generally difficult to observe, and if allowed render identification intractable.

### 3.2.3 Matching Strategy

We have described how our matching strategy combines nearest neighbor matching with exact matching to eliminate bias from the model. Here, we describe the specifics of this strategy.

The first dimension on which we require an exact match is the year in which the vehicle defining the treatment status of the household was purchased. As discussed earlier, the market penetration rate, gasoline prices, and federal policy incentives, which vary temporally, are important factors affecting hybrid (Prius) adoption. By requiring a hybrid (Prius) household to match to a non-hybrid (non-Prius) household that purchased a vehicle in the same year, we eliminate the effects of such time varying observable factors on hybrid (Prius) adoption, as well as other unobservable factors related to the purchase year of the vehicle.

The second dimension on which we require an exact match is the geographical area of residence, defined as either the CBSA or zip code. The former provides greater matching flexibility on other covariates by not requiring as precise of a geographic match, while the strength of the latter is that zip codes are more plausibly homogeneous than CBSAs. Restricting the matched households to reside within the same geographic area eliminates the possibility that the households face different social norms. For instance, certain areas (e.g., San Francisco) are known to attract households with greater social concern for the environment. By requiring a hybrid (Prius) household in San Francisco to be matched to a non-hybrid (non-Prius) household also in San Francisco we eliminate any effects that are unique to, but common throughout, San Francisco. Exact matching on geographical area also eliminates the effects of spatial variation in the market penetration rate, gasoline prices, policy incentives, population and urbanization characteristics, as well as other spatially varying factors.

The third dimension over which we require an exact match is the vehicle type or vehicle counterpart of the vehicle defining the treatment status of each household. An exact match on vehicle type ensures that a hybrid (Prius) household is matched to a non-hybrid (non-Prius) household that purchased a similar sized vehicle (i.e., a vehicle in the same class). In hybrid models, we also consider exactly matching hybrid households to those households that did not purchase a hybrid, but purchased a conventional engine counterpart of the hybrid. For example, we match a household that purchased a Honda Civic hybrid to a household that purchased a conventional engine Honda Civic. Following Sexton and

Sexton (2014), we match the Toyota Prius, which does not have a counterpart non-hybrid model, with the Toyota Corolla because the Corolla is the most similar Toyota model to the Prius. Through exact matching on hybrid counterparts, we account for unobservable factors that drive household vehicle choice.

Another dimension over which we conduct exact matching is frequency of internet use. Frequency of internet use captures unobservable preferences for new technology. The NHTS survey was conducted in 2008-2009, and records hybrid purchases over the 2000s decade. During this time period, daily internet use was not generally commonplace across all socio-economic groups. Low frequency of internet use indicates that the household has low openness and/or less access to new technology.

In addition to requiring an exact match along these dimensions, we use nearest neighbor matching on a number of household characteristics that could affect driving distance or hybrid (Prius) adoption, including income, household size, number of vehicles, average age of drivers in the household, share of female drivers in the household, work commute distance, the strength of local environmentalism, and the average MPG of other vehicles owned by the household. Finally, our initial attempt was to match on education via nearest neighbor, but we obtain a better post-match balance when imposing the exact match on education in the hybrid model. Hence, education is matched through nearest neighbor matching in Prius models but exact matching in hybrid models.

### 3.2.4 Why Not an IV Approach?

One possible approach to deal with the self-selection of hybrid (Prius) adoption is to use the federal tax deductions and credits as an instrumental variable, as these variables have been shown to be correlated with hybrid adoption at an aggregate level (Chandra et al. 2010, Beresteanu and Li 2011, Gallagher and Muehlegger 2011) and are plausibly exogenous to household driving behavior.[9] However, our preliminary regressions strongly indicate that the effects of these variables on hybrid (Prius) adoption are weak and unreliable when using household data. The weakness of these instruments comes from the

[9] State and local incentives also exist, but these variables are less credibly valid as instrumental variables as state and local policy incentives are likely correlated with general trends of environmental preferences within the state or local communities. Still, we experimented with these variables, which turned out to be less relevant than the federal incentive measures.

fact that there is no spatial variation in these incentives across households; the variation in these incentives is temporal, and as a result is collinear with gasoline prices, hybrid vehicle penetration rates in the automobile market, and a time trend. It is possible to estimate probit regressions in which the federal incentive measure is positive and significantly correlated with hybrid adoption (see the unpublished Supplemental Appendix), however, the significance is not stable across samples and model specifications. Furthermore, using the federal incentive directly as an instrumental variable in an IV-regression of annual miles traveled on hybrid ownership generates implausible coefficient estimates and standard errors, and does not pass standard tests of weak instruments.[10]

Moreover, hybrid (Prius) ownership is driven to a substantial degree by unobservable individual/household specific preferences, as well as community/social influence. Many households might be classified as never-takers of treatment; it is likely that there are no instrumental variables that can yield exogenous incentive for these consumers to purchase a hybrid. Similarly, certain consumers are always-takers; it is equally difficult to find any type of exogenous incentive that encourages these consumers to purchase a hybrid, since they are naturally pre-disposed to hybrid ownership. Sallee (2011) shows that government incentives do significantly correlate with the household decision to buy a hybrid; yet, it is not clear whether households simply time their purchases to coincide with a maximum incentive value, or whether the incentive independently induces hybrid purchase in a group of compliers. It is likely that the incentive both stimulates compliers to purchase a hybrid, but is also taken simply by consumers who would have purchased the hybrid regardless (Ozaki and Sevastyanova 2011). It is difficult to know how big the complier group is, and hence whether using policy incentives as instrumental variables is a promising empirical strategy.

For these reasons, we do not pursue an instrumental variables approach, and instead use the nonparametric matching approach outlined above to eliminate bias from both observable and unobservable factors that influence both hybrid (Prius) adoption and driving behavior.

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[10] For instance, the IV point estimate implies that hybrid households drive about 50,000 miles less per year compared to non-hybrid households.

# 4 Data Construction and Summary Statistics

## 4.1 Data Construction

The majority of our data comes from the 2009 National Household Travel Survey (NHTS), conducted by the U.S. Department of Transportation from March 2008 through May 2009. The original data contains 150,147 households, 309,163 vehicles, and 351,275 individual persons. Since our analysis is at the household level, the original data at the person and vehicle levels are aggregated to the household level. We also obtained quarterly data on the price of regular grade gasoline at the city level from 2000 to 2009 from the Council for Community and Economic Research, and the Green Plan Capacity (GPC) index from Resource Renewal Institute (Siy et al. 2001).

**Overview** Our data include variables measuring hybrid ownership and annual miles traveled by households, household demographic characteristics, characteristics of all vehicles owned by the household (e.g., make, model, year, odometer reading, etc.), and characteristics of regions in which the households live (e.g., both CBSA and zip code identifiers, as well as variables indicating urban/rural, availability of urban rail, population, etc.). We exclude all households with incomplete information on these variables. Since hybrid vehicles only appear in the sample after 2000, we limit our data to households who bought at least one brand new vehicle after 2000 to avoid any systematic differences that might exist between households that purchased a hybrid and households that purchased a new car prior to 2000.

In the NHTS survey, vehicles denoted as hybrids include gasoline-electric hybrid vehicles as well as vehicles using alternative fuels. We eliminate any vehicles that use alternative fuels but are not gasoline-electric hybrids; we compare NHTS information on the make/model/year of each vehicle with a list of all possible make/model/year combinations of gasoline-electric hybrid vehicles which we obtain from the Vehicle Make and Model book associated with the NHTS documentation, Edmunds.com, Hybridcars.com and Wikipedia in order to ensure that the hybrids kept in our sample are only gasoline-electrics.

Furthermore, we restrict our analysis to gasoline powered vehicles used for personal travel. This includes any vehicles classified as automobile/car/station wagon, van (minivan, cargo van, or passenger van), sport utility vehicle, and pickup truck, but excludes motorcycles, other trucks, golf carts, and other vehicles. The NHTS survey also includes an indicator for whether or not the vehicle has a commercial license plate; we remove all households that own any such vehicle. We also remove all households that own vehicles using diesel, natural gas or electricity, or fuel other than motor gasoline. Table 1 provides a list of variables used in our analysis, along with a brief description of each variable. Our dependent variable is annual miles traveled, and the independent variables include income, education, internet usage, commute distance, MPG of other vehicles in the household, the number of vehicles in the household, the number of household members, the age of drivers, percent of drivers that are female, geographic identifies (zip code and CBSA), vehicle type, the year the vehicle was purchased, and the Green Plan Capacity index that measures the strength of regional environmentalism.

**Additional Descriptive and Balancing Variables** In addition, we include a handful of other variables in the descriptive statistical analysis and balancing checks in the appendix.[11] We do not match on these variables directly because these variables are redundant in our set of matching covariates, and/or these variables do not improve the balance of our matched datasets. However, the balance on these variables helps to indicate the quality of our match, so we include these variables in our pre- and post-match balancing assessments. The unpublished Supplemental Appendix describes these variables in detail, so that our discussion here focuses exclusively on the variables we directly include in our set of matching covariates.

[11] These variables include a categorical variable for life cycle stage, an indicator for Hispanic ethnicity, a categorical measure of race, MSA-level descriptive indicators, an urban/rural indicator, the number of drivers and workers in the household, city-level gasoline prices, and state and federal tax incentives for hybrid adoption.

**Table 1: List of variables and definitions**

| Variable | Definition |
|---|---|
| Annual Miles Traveled | BESTMILE in the NHTS survey; is the NHTS's best estimate of household vehicle miles traveled and is based on self-reporting, odometer readings, and household demographic information. We exclude households for which BESTMILE is identified by the NHTS as an outlier. |
| Household Income | Total annual income of the household; spans 18 categories; divided into intervals of $5,000. Category 1 indicates annual household income of less than $5,000, and Category 2 indicates annual household income between $5,000 and $9,999, and the highest category, Category 18, indicates annual household income greater than $100,000. |
| Highest Education | A categorical variable, with values from 1 to 5 that represent: less than high school; high school or GED; some college, vocational, or an Associate's degree; a Bachelor's degree; and graduate or professional degree. We use the highest education level of any member in the household to capture the education level of the household. |
| Internet Usage | Indicator for whether at least one member in the household uses the internet almost every day; measures the household's attitude and access toward new technology. We use the frequency of the household member with the most frequent internet use to capture the highest frequency of internet use of the household. |
| Commute Distance | The sum of commute distance to work (i.e., mandatory travel) across all workers in each household. Any household with a single family member reporting a commute distance of more than 75 miles is dropped. |
| MPG of Other Vehicles | The composite city/highway MPG tested by US EPA; is the adjusted lab test MPG following the adjustment method used by the EIA to derive fuel consumption from the EPA composite MPG (EIA 2011). We further discount the NHTS MPG ratings by 15 percent to account for the difference between lab tested MPG and on road MPG. We construct the average MPG rating of vehicles in each household other than the one that defines the treatment status of the household. |
| Number of Vehicles | The number of vehicles owned by the household; excludes any motorcycles, other trucks, golf carts, etc. |
| Household Size | The total number of members in the household. |
| Age of Drivers | Average age of all drivers in the household. |

| | |
|---|---|
| Female | Percent of the drivers in the household who are female. |
| Zip Code | The zip code in which the household is a resident. |
| CBSA | The CBSA in which the household is a resident. |
| Vehicle Type | Type of the vehicle defining the treatment status of the household. A categorical variable, with values from 1 to 4 that represent automobile/station wagon, van, sports utility vehicle, and pickup truck. |
| Year Purchased | The year in which the household purchased the vehicle defining the treatment status of the household. |
| Green Plan Capacity (GPC) | Comes from Siy et al. 1999; measures the strength of environmentalism across different regions. The GPC index is defined on a 100-point scale, covering 65-indicators, and is calculated for each state in the U.S.; comprises four sub-indices: comprehensiveness of the environmental management framework; level of environmental policy innovation; fiscal and program commitment; and the quality of governance. |

Note: All data comes from the 2009 NHTS survey with the exception of the Green Plan Capacity index.

## 4.2 Descriptive Statistics

Table 2 provides descriptive statistics for the full sample, as well as the hybrid and Prius samples individually. Our final dataset includes 36,780 households. Of these, 35,495 households do not own a hybrid vehicle. Of the remaining 1,285 households that own a hybrid vehicle, 696 own a Prius. We report in the unpublished Supplemental Appendix the sample distribution of all hybrid makes and models. The Toyota Prius is the most popular hybrid model, contributing to 53.5 percent of the hybrids in our dataset, while the next most popular hybrids are the Honda Civic, Toyota Camry, Toyota Highlander, Ford Escape and Honda Accord hybrids.

From Table 2, we see that the average household drives about 26,636 miles per year; the average hybrid household drives slightly more miles per year (27,914). Prius households average more miles than the full sample, but fewer miles than the hybrid sample (27,259). Further, in the full sample of households, about 3 percent own a hybrid vehicle.

Hybrid households average a higher income and education, are more frequent internet users, average longer commutes, and live in more environment friendly states. Further, hybrid households average higher MPG ratings on other vehicles in the household, which provides some indication that hybrid households have stronger preferences for fuel efficiency.

**Table 2: Descriptive Statistics**

| Statistic | All Households | | Hybrid Households | | Prius Households | |
|---|---|---|---|---|---|---|
| | Mean | Std. Dev. | Mean | Std. Dev. | Mean | Std. Dev. |
| Hybrid/Prius Indicator[a] | 0.03 | 0.18 | 0.54 | 0.50 | | |
| Annual Miles Traveled | 26,636 | 14,495 | 27,914 | 14,461 | 27,259 | 13,391 |
| Household Income[a] | | | | | | |
| Below $50,000 | 0.26 | 0.44 | 0.12 | 0.32 | 0.12 | 0.32 |
| $50,000-$99,999 | 0.41 | 0.49 | 0.32 | 0.47 | 0.33 | 0.47 |
| $100,000 and above | 0.33 | 0.47 | 0.57 | 0.50 | 0.55 | 0.50 |
| Highest Education[a] | | | | | | |
| Less than high school | 0.01 | 0.10 | 0.003 | 0.06 | 0.001 | 0.04 |
| High school | 0.13 | 0.34 | 0.03 | 0.18 | 0.02 | 0.15 |
| Associate’s degree | 0.25 | 0.43 | 0.14 | 0.35 | 0.13 | 0.33 |
| Bachelor’s degree | 0.30 | 0.46 | 0.27 | 0.44 | 0.24 | 0.43 |
| Graduate degree | 0.31 | 0.46 | 0.55 | 0.50 | 0.61 | 0.49 |
| No. of Vehicles | 2.35 | 0.64 | 2.35 | 0.65 | 2.37 | 0.65 |
| Household Size | 2.69 | 1.12 | 2.62 | 0.98 | 2.57 | 0.96 |
| No. of Drivers | 2.12 | 0.54 | 2.12 | 0.53 | 2.14 | 0.55 |
| Average Age of Drivers | 53.31 | 14.06 | 53.31 | 12.85 | 54.47 | 13.06 |
| Share of Female Drivers | 0.51 | 0.23 | 0.50 | 0.21 | 0.50 | 0.20 |
| Internet Usage[a] | 0.83 | 0.38 | 0.94 | 0.24 | 0.95 | 0.22 |
| Commute Distance[b] | 14.61 | 17.73 | 16.48 | 18.98 | 16.20 | 18.72 |
| Year Purchased | 2,005.49 | 1.97 | 2,006.32 | 1.48 | 2,006.16 | 1.54 |
| Vehicle Type[a] | | | | | | |
| Auto/Station Wagon | 0.49 | 0.50 | 0.82 | 0.38 | 1.00 | 0.00 |
| Van | 0.09 | 0.29 | 0.00 | 0.00 | 0.00 | 0.00 |
| Sport Utility Vehicle | 0.28 | 0.45 | 0.18 | 0.38 | 0.00 | 0.00 |
| Pickup Truck | 0.14 | 0.34 | 0.002 | 0.04 | 0.00 | 0.00 |
| MPG of Other Vehicles | 21.21 | 4.55 | 23.20 | 7.34 | 23.90 | 7.63 |
| GPC Index | 37.71 | 7.33 | 38.69 | 6.99 | 38.88 | 7.35 |
| Observations | 36,780 | | 1,285 | | 696 | |

[a] Binary variable(s); the reported means correspond to the percentage of observations in the sample that receive a value of 1.
[b] Commute distance is in miles.

# 5 Covariate Matching Results

## 5.1 Metrics to Assess Balance and Overlap

Prior to implementing our matching estimator, we assess overall balance and overlap for treated households versus control households – that is, Prius hybrid households versus non-Prius hybrid households, and hybrid households versus non-hybrid households.

**The Normalized Difference** The first metric we use to assess balance is the normalized difference

$$ND_{1,0} = \frac{\bar{x}_1 - \bar{x}_0}{\sqrt{(\sigma_1^2 + \sigma_0^2)/2}} \tag{4}$$

in which $\bar{x}$ denotes the mean, $\sigma^2$ denotes the variance, and the subscripts 1 and 0 indicate the treated and control samples, respectively. The normalized difference provides a unit free measure of dispersion of the means of the two samples, and is calculated using the sample average and sample variance. To provide some perspective, a normalized difference measure lower than 0.1 is in line with "what one might expect in a completely randomized experiment" and linear regression models may have difficulty adjusting for imbalance when the normalized difference is above 0.25 (Imbens and Rubin 2015, p. 352).

**The Log Ratio of Standard Deviations** While the normalized difference measures differences in the central tendencies of the covariate distributions across treated/control samples, the log ratio of standard deviations measures the difference in dispersions of the two distributions. This measure is given by

$$\Gamma_{1,0} = \log(\sigma_1) - \log(\sigma_0) \tag{5}$$

where $\sigma$ denotes the standard deviation and is calculated using sample standard deviations. The larger the value of $\Gamma_{1,0}$ for any particular covariate, the larger the difference in distributional dispersion, which indicates greater difficulty in adjusting for biases.

**The Fraction of Observations in the Tails of the Opposing Distribution** One way to assess whether there is sufficient overlap in the distributions of covariates is through the fraction of observations in the treated/control group that lie in the tails of the distribution for the opposing group. The larger this fraction, the more difficult it will be to find a corresponding observation in the opposing group for the match. For the treated group we calculate this percentage via

$$\pi_1^\alpha = \left[1 - F_1\left(F_0^{-1}(1 - \alpha/2)\right)\right] + F_1\left(F_0^{-1}(\alpha/2)\right) \tag{6}$$

for significance level $\alpha = 0.05$ and distribution functions $F(\cdot)$. The calculation for the control group is similar.

## 5.2 Pre-Match Assessment of Balance and Overlap

We report the results for our pre-match balance and overlap assessments in Appendix A, Tables A1-A2. For the Prius treatment model, we use the set of 1,285 hybrid owning households, of which 696 households own a Prius and the remaining 589 households own other hybrid models. For the hybrid treatment model, we use the full sample of 36,780 households, of which 1,285 households own a gasoline-electric hybrid and 35,495 households do not.

There are a few significant differences between Prius and non-Prius hybrid samples pre-match. The largest normalized differences are in terms of vehicle type, year purchased, MPG of other vehicles, and education. The other metrics indicate there is sufficient overlap to restore balance via matching.[12]

There are more substantial differences between hybrid and non-hybrid households along several important dimensions. The normalized difference for household income, education, internet usage, hybrid market penetration rate, gasoline price, year purchased, the MPG of other household vehicles, vehicle type, and MSA characteristics are all substantially higher than 0.25. These measures suggest that estimates that do not adjust for these differences – particularly, linear regression methods – are likely to be biased.

The other metrics indicate that it is feasible to restore balance via matching. The log difference in standard deviations and percent of observations in the tails of the opposing treatment group are all relatively low, indicating substantial overlap in the distributions of

[12] The values of the fractions of observations in the tails of the opposing distribution for several categorical variables are high. However, for categorical variables, a high value need not indicate a lack of overlap given that the data all fall into a few, countable bins.

these covariates between hybrid and non-hybrid samples. The overlap comes from the large number of non-hybrid (control) households in the NHTS survey.

### 5.3 Is There A Social Status Rebound Effect?

We report our matching estimates of the $ATT$ for the social status driven rebound effect in Table 3. Due to the relatively small sample size of the hybrid households, we are not able to conduct matching at the zip code level in the Prius model so we only require an exact match at the CBSA level. The rest of the matching is as described previously, in which vehicle type, internet usage, and purchase year are exactly matched, and household income, size, the number of vehicles, commute distance to work, the average age of drivers, the share of female drivers in the household, and the average fuel efficiency of other vehicles in the household are matched to the nearest neighbor. Finally, Model 1 includes households that are not located in a CBSA, requiring an exact match to another household also not in a CBSA but located within states with the closest GPC index (with the similar green plan capacity), while Model 2 eliminates households not located in a CBSA.

We find that in both models, the treatment effect estimates are not significant, which indicates that the annual miles traveled for the average Prius household is not significantly different from that of the average counterfactual non-Prius hybrid household. Hence, despite the social status signaling ability of the Toyota Prius, we do not find statistical evidence of a behavioral response that capitalizes on the status signal value in terms of annual miles traveled. In other words, while the environmental signal ability of visually distinctive hybrids increases the exposure of hybrid vehicles and is capitalized in their sale price (Delgado et al 2015), the same visual distinctiveness does not induce any increase in miles traveled and fuel consumption.

**Table 3: Matching Estimates of the Effect of the Prius Ownership on Annual Miles Traveled**

| | Model 1 | Model 2 |
|---|---|---|
| *CBSA Level* | | |
| Estimate | -962.680 | -683.343 |
| Standard Error | 590.454 | 590.819 |
| No. of Matched Hybrids | 338 | 330 |

The reported estimates and standard errors are Abadie and Imbens (2011) bias-corrected estimates. An exact match is required for year of purchase, vehicle type, frequency of internet usage, and CBSA. Matching on other covariates uses nearest neighbor matching using the Mahalanobis distance metric. One matched control unit is allowed for each treated unit. Model 1 includes observations that are not in a CBSA, and Model 2 excludes observations that are not located in a CBSA.

### 5.4 The Effect of Hybrid Ownership on Annual Miles Traveled

We next turn to the total rebound effect associated with owning a hybrid vehicle (of any kind). Our matching estimates of the effect of hybrid ownership on annual miles traveled are reported in Table 4. In the top two panels, we require an exact match at the CBSA level; the top panel further requires an exact match on vehicle type, and the middle panel further restricts the match to the exact conventional engine vehicle counterpart. Given the richness of our data on non-hybrid households, we are able to match hybrid households with non-hybrid households living in the same zip code area so the bottom panel restricts the exact match to the zip code level. Nevertheless, the zip code level match is restrictive, and so for these specifications we only restrict the exact match to vehicle type and not to the conventional engine counterpart. The rest of the matching is the same as the Prius model.

We view the combination of the models shown in Table 4 as complementary. Matching on zip code or excluding households not in a CBSA tightens the geographical area match and thus better controls for the influence of local social norms; matching on the counterpart of each hybrid improves the match in terms of households' preferences related to brand, style, etc.; matching on CBSA, including households not in a CBSA, and/or matching on vehicle type increases the possibility of a successful match in other directions.

We find that in most of the models we estimate, hybrid-ownership causes households to drive more miles per year. Our estimates of the causal effect range from just under 400 miles per year to just over 785 miles per year. For example, the top panel estimate for

Model 2 implies that a household that owns a hybrid, on average, drives 772 miles more per year than a non-hybrid-owning household that purchased a new vehicle with the same type in the same year, resides in the exact same CBSA, has the same (or at least very similar) preferences on lower travel cost and/or environmental preservation and household demographics, and has the similar other household characteristics related to hybrid adoption and driving behavior. The only insignificant rebound effect comes from the model matching on CBSA, non-hybrid counterparts, and excluding households not in a CBSA.

**Table 4: Matching Estimates of the Effect of Hybrid Ownership on Annual Miles Traveled**

| | Model 1 | Model 2 |
|---|---|---|
| *CBSA Level (Vehicle Type)* | | |
| Estimate | 786.978* | 772.432* |
| Standard Error | 436.140 | 436.267 |
| No. of Matched Hybrids | 1072 | 1036 |
| *CBSA Level (Counterpart)* | | |
| Estimate | 749.873** | 398.077 |
| Standard Error | 339.485 | 340.082 |
| No. of Matched Hybrids | 451 | 434 |
| *Zip Code Level (Vehicle Type)* | | |
| Estimate | 521.638** | |
| Standard Error | 249.826 | |
| No. of Matched Hybrids | 299 | |

The reported estimates and standard errors are Abadie and Imbens (2011) bias-corrected estimates. An exact match is required for household education, year of purchase, frequency of internet usage, vehicle type or counterpart, and CBSA or zip code. Matching on other covariates uses nearest neighbor matching using the Mahalanobis distance metric. One matched control unit is allowed for each treated unit. CBSA Model 1 includes observations that are not in a CBSA, and CBSA Model 2 excludes observations that are not located in a CBSA.

### 5.5 Post-Match Balance and Overlap Assessment

The credibility of these estimates as causal effects depends critically on whether the matching procedure is able to restore balance to the covariate distributions. We report post-match balancing statistics for the estimates from Tables 3 and 4 in Appendix B (Tables B1-B4).

We find that several covariates in the Prius treatment model have post-match normalized differences that are below 0.25 but above 0.1 (the largest is household income at -0.203 and -0.242 in Models 1 and 2). While these post-match statistics are not necessarily indicative of bias, we explore further to guard against the possibility of bias. We run a linear regression to estimate the effect of Prius treatment on annual miles traveled using the matched sample. The regression on matched data provides a straightforward means of further adjusting for observable covariates within the matched sample; it is important to use the matched sample for these regressions because the unmatched sample is too imbalanced to reliably support a linear regression (Imbens and Rubin 2015). Despite these additional adjustments, we continue to find that Prius treatment is not significant (see the unpublished Supplemental Appendix).

For the hybrid treatment model, the normalized difference between the treated and control units is nearly zero (below 0.10) for most of the covariates across each of the specifications, indicating little chance that these covariates induce bias into our estimates. The most difficult covariate to get into balance is the average MPG of other vehicles. It is clear from these post-match balancing tables that the normalized difference for this covariate is greatly reduced via the matching procedure. It becomes below 0.1 in the models matching hybrids to their conventional engine counterparts; in other models it is always below 0.20. Kernel density estimates (unpublished Supplemental Appendix) show that there are virtually no distributional differences between hybrid and non-hybrid households for the covariate even when the normalized difference for this covariate is above 0.1. Hence, even in the cases in which this covariate is not perfectly balanced, there is little chance that this variable causes bias in our estimates.

## 6 Policy Implications: Hybrid Ownership and Gasoline Consumption

The causal estimate of the impact of hybrid ownership on annual miles traveled has direct implications for policies that seek to reduce gasoline consumption and corresponding greenhouse gas emissions via hybrid vehicle adoption. The reduction in fuel consumption is determined by the increase in hybrid fuel efficiency relative to conventional engine vehicles and the size of the hybrid rebound effects in miles traveled:

$$
\begin{aligned}
&\mathit{Proportional\ reduction\ in\ fuel\ consumption}\\
&= \frac{VMT_{non}/_{MPG_{non}} - (VMT_{non} + \Delta\, VMT)/_{(MPG_{non} + \Delta\, MPG)}}{VMT_{non}/_{MPG_{non}}}\\
&= 1 - \frac{(1 + \Delta\, VMT/VMT_{non})}{(1 + \Delta\, MPG/MPG_{non})} \qquad (7)
\end{aligned}
$$

where $\Delta VMT$ is the change in vehicle miles traveled following hybrid adoption, $\Delta MPG$ is the increase in fuel efficiency from the non-hybrid to the hybrid, $VMT_{non}$ is miles traveled in the absence of hybrid ownership, and $MPG_{non}$ is the fuel efficiency of a non-hybrid vehicle. The change in miles traveled is calculated using rebound effect estimates from Table 4, and the increase in fuel efficiency is calculated based on the difference in fuel efficiency between hybrid and non-hybrid vehicles. To be consistent with the estimates of the rebound effect, we only use the fuel efficiency of the vehicle that defines the treatment status of each household when we calculate fuel efficiency of hybrid and non-hybrid vehicles. We calculate the reduction in fuel consumption (as a proportion) for each rebound effect model in Table 4 using Equation (7) and report these results in Table 5. To be consistent with the $ATT$ measurement, we calculate all values only based on the matched samples. Since the matched household pairs differ across models, the increases in fuel efficiency and miles traveled are (slightly) different across models.

The average increase in fuel efficiency realized by a switch from a non-hybrid counterpart to a hybrid are 55.8 and 56.0 percent for the counterpart models in Table 4. These values are lower than the increases in fuel efficiency in the other models, since the hybrid vehicle counterparts are typically smaller and more fuel efficient compared to the average of all non-hybrid vehicles. Table 5 shows that the estimates of a reduction in fuel consumption in counterpart models are also smaller, at 34.1 and 35 percent, which provides a lower bound for the reduction in fuel consumption via hybrid adoption, assuming that only those households that purchased a counterpart model of a certain hybrid would otherwise purchase the hybrid (after controlling for all other influencing factors).

When considering the models that match on vehicle type, we find the average fuel efficiency increase from non-hybrid to hybrid is about 89 percent, and the corresponding reduction in fuel consumption is about 46 percent. The estimates from these models provide upper bounds for the reduction in fuel consumption via hybrid adoption, under the assumption that households that purchased a non-hybrid vehicle purchased a vehicle of the same type as their counterfactual hybrid (i.e., had they purchased a hybrid).

**Table 5: Estimates of the Reduction in Fuel Consumption from Hybrid Vehicle Adoption**

| | Model 1 | Model 2 |
|---|---|---|
| *CBSA Level (Vehicle Type)* | | |
| Increase in fuel efficiency for hybrid vehicles | 89.1% | 89.2% |
| Increase in miles traveled for hybrid households | 2.9% | 2.9% |
| Reduction in fuel consumption from hybrid adoption | 45.6% | 45.6% |
| *CBSA Level (Counterpart)* | | |
| Increase in fuel efficiency for hybrid vehicles | 55.8% | 56.0% |
| Increase in miles traveled for hybrid households | 2.7% | 1.4% |
| Reduction in fuel consumption from hybrid adoption | 34.1% | 35.0% |
| *Zip Code Level (Vehicle Type)* | | |
| Increase in fuel efficiency for hybrid vehicles | 89.1% | |
| Increase in miles traveled for hybrid households | 1.8% | |
| Reduction in fuel consumption from hybrid adoption | 46.2% | |

Note that the Model 2 estimates for the *CBSA Counterpart* specification are based on statistically insignificant *ATT* estimates (Table 3).

To compare our results with the previous studies' estimates of the rebound effect, we translate our results into the elasticity of an increase in miles traveled with respect to an increase in fuel efficiency or a decrease in fuel cost, which is the most widely calculated rebound effect. Matched households in our models face the same gasoline price, because they are exactly matched on location of residence and vehicle purchase year; hence the only difference in fuel cost comes from the difference in fuel efficiency between the vehicles. We translate our smallest and largest estimates into these rebound effect estimates to provide a range of rebound effects based on our estimates.

Our smallest estimate comes from the insignificant estimate of miles traveled coming from hybrid adoption (Table 4, Model 2); the insignificance indicates that the rebound effect coming from an increase in fuel efficiency and a decrease in fuel cost is indistinguishable from zero. The greatest estimate is from the model with a 2.7 percent increase in miles traveled (Table 4, Model 1), in response to a 55.8 percent increase in fuel efficiency. If we translate this figure to the elasticity of miles traveled in response to a change in fuel efficiency, a 100 percent increase in fuel efficiency leads to a 4.8 percent increase in miles traveled (which comes from $2.7/55.8 \times 100 = 4.8$). If we translate the same figure to the elasticity of miles traveled in response to a change in travel cost per mile, when the fuel efficiency of a hybrid increases by 55.8 percent, travel cost per mile decreases by 35.8 percent.[13] With the increase in miles traveled being 2.7 percent, a 100 percent decrease in fuel cost leads to an increase in travel distance by 7.5 percent (coming from $2.7/35.8 \times 100 = 7.5$). Hence, our estimates of the rebound effect elasticities with respect to an increase of fuel efficiency range from 0 to 4.8 percent; our estimates of the rebound effect coming from a decrease in fuel cost range from 0 to 7.5 percent.

Our estimates of the hybrid rebound effect are similar to previous findings based on non-hybrid vehicles. For the rebound effect associated with increase in fuel efficiency, Greene (2012) finds that the rebound effect of fuel economy on vehicle miles traveled is not significant, and De Borger et al. (2016) calculate the rebound effect to be 7.5-10 percent. For the rebound effect associated with a reduction in travel cost, Small and Van Dender (2007) estimate a short term rebound effect of 2.2 percent, and a long term rebound effect of 10.7 percent. The short term and long term estimates from Hymel et al. (2010) are 4.7 and 24.1 percent. Our findings are also consistent with the conclusions of Gillingham et al. (2013) in that rebound effects, if they exist, are not large enough to offset the environmental gains that stem from the improved efficiency.

## 7 Conclusion

We estimate the causal impact of hybrid ownership on household annual miles traveled in order to understand how hybrid ownership impacts fuel consumption. Specifically, we examine two rebound effects: whether there is a significant social status driven rebound effect associated with visually distinct hybrids, and whether households drive more due to

[13] Travel cost per mile is given by the price of fuel per gallon times the inverse of fuel efficiency (the inverse of MPG). An increase of 55.8 percent in MPG translates to a reduction in travel cost per mile of 35.8 percent, holding the price of fuel per gallon constant.

hybrid adoption. Our research has important implications for environmental policy related to vehicle miles traveled and gasoline consumption: post assessment of the effects of policies encouraging the adoption of hybrids during the 2000's decade; the potential impacts of policies that encourage the adoption of fully electric vehicles have on vehicle miles traveled; and the effects of tightening the Corporate Average Fuel Economy (CAFE) standards which foster the proliferation of gasoline-electric hybrids to raise fleet fuel economy.

We do not find any evidence of a statistically significant social status rebound effect associated with ownership of visually distinct hybrid vehicles: in our sample the visual distinctiveness of the Toyota Prius does not induce any increase in miles traveled and fuel consumption. We do find a statistically significant causal total rebound effect due to the adoption of a hybrid (of any kind): owning a hybrid vehicle causes a household to drive more miles per year, on average, than a counterfactual household that does not own a hybrid. However, this rebound effect is only about 3 percent of the total average annual miles traveled, and is insufficient to offset the reduction in fuel consumption due to the higher fuel efficiency of the gasoline-electric hybrid engine. We conclude that the rebound effect associated with hybrid adoption is small, and hybrid adoption reduces gasoline consumption for personal transportation by about 34 to 46 percent.

Our ability to interpret these estimates as causal effects rests on whether or not there remain any significant post-estimation differences between treated and control groups. Given the richness of the NHTS data and the large pool of non-hybrid households, we are able to eliminate virtually all statistical differences that exist pre-match. All post-matching balance assessments indicate that there is virtually no difference between matched samples; hence, our interpretation is causal.

As a final point, we do not model intra-household vehicle substitution because we focus on total household miles traveled. Because hybrids are generally more fuel-efficient than traditional gasoline powered vehicles, it is possible that a hybrid-owning household drives the hybrid selectively. We leave this issue for future research.

## Appendix A: Pre-Match Balance and Overlap Assessment

Here we report the results for our pre-match balance and overlap assessments for the Prius treatment model in Table A1 and the hybrid treatment model in Table A2. Recall that for the Prius treatment model, we use the set of 1,285 hybrids, of which 696 are Priuses (treated) and the remaining 589 are non-Prius hybrids (controls). For the hybrid treatment model, we use the full sample of 36,780 observations, of which 1,285 are hybrids (treated) and 35,495 are non-hybrids (controls).

**Table A1**: Pre-match Balance and Overlap Assessment – Prius Treatment

| Covariate | Prius Households Mean | Prius Households Std. Dev. | Non-Prius Households Mean | Non-Prius Households Std. Dev. | Normalized Difference | Log Diff. of Std. Dev. | % Prius in Tails | % Non-Prius in Tails |
|---|---|---|---|---|---|---|---|---|
| Vehicle Type | 1.000 | 0.000 | 1.754 | 0.975 | -1.093 | --[14] | 1.000 | 1.000 |
| Year Purchased | 2006.161 | 1.541 | 2006.497 | 1.396 | -0.229 | 0.099 | 0.057 | 0.022 |
| MPG of Other Vehicles | 23.896 | 7.634 | 21.933 | 5.309 | 0.298 | 0.363 | 0.076 | 0.056 |
| Household Income | 15.809 | 3.496 | 15.930 | 3.438 | -0.035 | 0.017 | 0.037 | 0.025 |
| Education | 4.431 | 0.809 | 4.226 | 0.912 | 0.238 | -0.120 | 0.024 | 0.211 |
| Internet Usage | 0.951 | 0.216 | 0.929 | 0.258 | 0.095 | -0.177 | 0.049 | 0.071 |
| Commute Distance | 16.195 | 18.723 | 16.807 | 19.280 | -0.032 | -0.029 | 0.322 | 0.282 |
| No. Vehicles | 2.368 | 0.655 | 2.336 | 0.635 | 0.049 | 0.030 | 0.724 | 0.745 |
| Average Age of Drivers | 54.474 | 13.063 | 51.945 | 12.469 | 0.198 | 0.047 | 0.086 | 0.041 |
| Share of Female Drivers | 0.503 | 0.201 | 0.496 | 0.218 | 0.036 | -0.080 | 0.073 | 0.095 |
| Household Size | 2.575 | 0.957 | 2.667 | 1.016 | -0.094 | -0.060 | 0.045 | 0.053 |
| No. Workers | 1.295 | 0.898 | 1.297 | 0.834 | -0.003 | 0.074 | 0.237 | 0.197 |
| No. Drivers | 2.138 | 0.545 | 2.109 | 0.520 | 0.055 | 0.048 | 0.078 | 0.056 |
| Life Cycle | 5.898 | 3.372 | 5.625 | 3.250 | 0.082 | 0.037 | 0.341 | 0.338 |
| Race | 1.249 | 1.006 | 1.368 | 1.278 | -0.104 | -0.239 | 0.922 | 0.944 |
| Hispanic | 0.045 | 0.206 | 0.058 | 0.233 | -0.060 | -0.123 | 0.955 | 0.942 |
| Market Penetration Rate | 0.017 | 0.013 | 0.017 | 0.013 | 0.022 | 0.016 | 0.046 | 0.041 |
| Gas Price (Purchase) | 2.581 | 0.593 | 2.635 | 0.556 | -0.094 | 0.064 | 0.059 | 0.049 |
| Gas Price (Survey) | 3.598 | 0.206 | 3.564 | 0.202 | 0.168 | 0.019 | 0.053 | 0.053 |
| MSA Category | 2.195 | 1.010 | 2.209 | 0.949 | -0.014 | 0.063 | 0.306 | 0.261 |
| Rail in MSA | 0.306 | 0.461 | 0.261 | 0.440 | 0.099 | 0.047 | 0.694 | 0.739 |
| Urban | 0.747 | 0.435 | 0.771 | 0.421 | -0.055 | 0.033 | 0.253 | 0.229 |
| GPC Index | 38.882 | 7.353 | 38.470 | 6.527 | 0.059 | 0.119 | 0.069 | 0.036 |

[14] The log ratio of standard deviations for vehicle type is infinite, since the standard deviation of treated hybrid households is 0.

**Table A2**: Pre-match Balance and Overlap Assessment – Hybrid Treatment

| Covariate | Hybrid Households Mean | Hybrid Households Std. Dev. | Non-Hybrid Households Mean | Non-Hybrid Households Std. Dev. | Normalized Difference | Log Diff. of Std. Dev. | % Hybrid in Tails | % Non-Hybrid in Tails |
|---|---|---|---|---|---|---|---|---|
| Vehicle Type | 1.358 | 0.770 | 2.079 | 1.148 | -0.737 | -0.400 | 0.822 | 0.623 |
| Year Purchased | 2006.315 | 1.485 | 2005.463 | 1.984 | 0.486 | -0.290 | 0.005 | 0.190 |
| MPG of Other Vehicles | 23.201 | 7.342 | 21.142 | 4.402 | 0.340 | 0.512 | 0.096 | 0.043 |
| Household Income | 15.865 | 3.469 | 13.853 | 4.515 | 0.500 | -0.264 | 0.011 | 0.094 |
| Education | 4.337 | 0.863 | 3.746 | 1.065 | 0.609 | -0.210 | 0.037 | 0.147 |
| Internet Usage | 0.941 | 0.236 | 0.825 | 0.380 | 0.366 | -0.476 | 0.059 | 0.175 |
| Commute Distance | 16.475 | 18.975 | 14.543 | 17.681 | 0.105 | 0.071 | 0.305 | 0.323 |
| No. Vehicles | 2.353 | 0.646 | 2.353 | 0.642 | 0.001 | 0.006 | 0.734 | 0.732 |
| Average Age of Drivers | 53.315 | 12.852 | 53.310 | 14.098 | 0.000 | -0.093 | 0.026 | 0.087 |
| Share of Female Drivers | 0.500 | 0.209 | 0.511 | 0.229 | -0.052 | -0.088 | 0.083 | 0.087 |
| Household Size | 2.617 | 0.985 | 2.696 | 1.128 | -0.074 | -0.136 | 0.048 | 0.066 |
| No. Workers | 1.296 | 0.869 | 1.210 | 0.877 | 0.098 | -0.010 | 0.219 | 0.248 |
| No. Drivers | 2.125 | 0.534 | 2.116 | 0.544 | 0.015 | -0.018 | 0.055 | 0.090 |
| Life Cycle | 5.773 | 3.318 | 5.991 | 3.340 | -0.066 | -0.007 | 0.339 | 0.301 |
| Race | 1.304 | 1.140 | 1.291 | 1.106 | 0.011 | 0.031 | 0.928 | 0.923 |
| Hispanic | 0.051 | 0.219 | 0.052 | 0.222 | -0.007 | -0.014 | 0.949 | 0.948 |
| Market Penetration Rate | 0.017 | 0.013 | 0.011 | 0.010 | 0.577 | 0.262 | 0.114 | 0.125 |
| Gas Price (Purchase) | 2.606 | 0.577 | 2.315 | 0.659 | 0.471 | -0.133 | 0.042 | 0.140 |
| Gas Price (Survey) | 3.582 | 0.204 | 3.505 | 0.169 | 0.413 | 0.188 | 0.047 | 0.043 |
| MSA Category | 2.202 | 0.982 | 2.505 | 0.980 | -0.309 | 0.002 | 0.286 | 0.169 |
| Rail in MSA | 0.286 | 0.452 | 0.169 | 0.375 | 0.280 | 0.186 | 0.714 | 0.831 |
| Urban | 0.758 | 0.428 | 0.696 | 0.460 | 0.140 | -0.071 | 0.242 | 0.304 |
| GPC Index | 38.693 | 6.987 | 37.679 | 7.336 | 0.142 | -0.049 | 0.029 | 0.056 |

## Appendix B: Post-Match Balance and Overlap Assessment

Tables B1 through B4 report normalized differences and log ratios of standard deviations for all covariates for the post-match samples.

**Table B1**: Post-match Balancing and Overlap Assessment for CBSA Level Matching Model – Prius Treatment

| Covariate | Model 1 | | Model 2 | |
|---|---|---|---|---|
| Vehicle Type | 0.000 | 0.000 | 0.000 | 0.000 |
| Year Purchased | 0.000 | 0.000 | 0.000 | 0.000 |
| MPG of Other Vehicles | 0.179 | 0.230 | 0.163 | 0.240 |
| Household Income | -0.203 | 0.143 | -0.242 | 0.203 |
| Education | 0.032 | 0.110 | -0.013 | 0.152 |
| Internet Usage | 0.000 | 0.000 | 0.000 | 0.000 |
| Commute Distance | -0.097 | 0.062 | -0.093 | 0.053 |
| No. of Vehicles | 0.106 | 0.096 | 0.110 | 0.100 |
| Average Age of Drivers | 0.197 | 0.178 | 0.188 | 0.167 |
| Share of Female Drivers | 0.015 | 0.195 | 0.015 | 0.195 |
| Household Size | -0.199 | -0.079 | -0.203 | -0.085 |
| No. of Workers | -0.202 | 0.183 | -0.174 | 0.172 |
| No. of Drivers | -0.006 | 0.151 | -0.013 | 0.135 |
| Life Cycle | -0.007 | 0.071 | -0.026 | 0.068 |
| Race | -0.045 | 0.019 | -0.046 | 0.020 |
| Hispanic | 0.184 | 0.427 | 0.187 | 0.426 |
| Market Penetration Rate | 0.046 | 0.045 | 0.048 | 0.036 |
| Gas Price (Purchase) | 0.082 | 0.043 | 0.071 | 0.026 |
| Gas Price (Survey) | -0.019 | 0.004 | -0.004 | -0.002 |
| MSA Category | -0.003 | 0.005 | 0.008 | 0.017 |
| Rail in MSA | 0.012 | 0.001 | 0.006 | 0.001 |
| Urban | -0.093 | 0.079 | -0.125 | 0.120 |
| GPC Index | -0.022 | 0.106 | -0.035 | -0.095 |
| CBSA | 0.000 | 0.000 | 0.000 | 0.000 |

Post-match normalized difference and log ratio of standard deviation statistics for the matched estimates reported in Table 3. An exact match is required for year of hybrid purchase, vehicle type, frequency of internet use and CBSA. One-to-one nearest neighbor matches using the Mahalanobis distance metric was required for household income, size, vehicle count, MPG of other vehicles, highest education, commute distance, age, share of female, and GPC index. Model 1 allows for households outside of CBSA to be matched, and Model 2 focuses only on households within a CBSA. See notes to Table 3 and text for further details.

**Table B2**: Post-match Balancing Assessment for CBSA and Vehicle Type Matching Model – Hybrid Treatment

| Covariate | Model 1 | | Model 2 | |
|---|---|---|---|---|
| Vehicle Type | 0.000 | 0.000 | 0.000 | 0.000 |
| Year Purchased | 0.000 | 0.000 | 0.000 | 0.000 |
| MPG of Other Vehicles | 0.176 | 0.301 | 0.167 | 0.302 |
| Household Income | -0.028 | 0.063 | -0.036 | 0.067 |
| Education | 0.000 | 0.000 | 0.000 | 0.000 |
| Internet Usage | 0.000 | 0.000 | 0.000 | 0.000 |
| Commute Distance | 0.080 | 0.206 | 0.074 | 0.191 |
| No. of Vehicles | 0.082 | 0.152 | 0.078 | 0.149 |
| Average Age of Drivers | -0.052 | 0.028 | -0.049 | 0.028 |
| Share of Female Drivers | 0.029 | 0.266 | 0.030 | 0.262 |
| Household Size | 0.049 | 0.072 | 0.051 | 0.080 |
| No. of Workers | -0.080 | 0.024 | -0.083 | 0.026 |
| No. of Drivers | -0.031 | 0.147 | -0.028 | 0.150 |
| Life Cycle | 0.003 | -0.029 | 0.012 | -0.026 |
| Race | 0.061 | 0.170 | 0.057 | 0.165 |
| Hispanic | 0.013 | 0.026 | 0.009 | 0.017 |
| Market Penetration Rate | -0.002 | 0.000 | -0.005 | -0.004 |
| Gas Price (Purchase) | -0.011 | -0.018 | -0.015 | -0.019 |
| Gas Price (Survey) | 0.002 | -0.001 | 0.002 | -0.002 |
| MSA Category | -0.006 | 0.000 | -0.005 | -0.003 |
| Rail in MSA | 0.002 | 0.001 | 0.000 | 0.000 |
| Urban | 0.011 | -0.007 | 0.021 | -0.015 |
| GPC Index | -0.003 | -0.012 | -0.018 | -0.053 |
| CBSA | 0.000 | 0.000 | 0.000 | 0.000 |

Post-match normalized difference and log ratio of standard deviation statistics for the matched estimates reported in Table 3. An exact match is required for household education, frequency of Internet usage, year of hybrid purchase, vehicle type, and CBSA. Nearest neighbor matches using the Mahalanobis distance metric was required for household income, size, vehicle count, MPG of other vehicles, commute distance, age, share of female, and GPC index. See the notes to Table 4 and text for further details.

**Table B3**: Post-match Balancing Assessment for CBSA and Counterpart Matching Model – Hybrid Treatment

| Covariate | Model 1 | | Model 2 | |
|---|---|---|---|---|
| Counterparts | 0.000 | 0.000 | 0.000 | 0.000 |
| Year Purchased | 0.000 | 0.000 | 0.000 | 0.000 |
| MPG of Other Vehicles | 0.067 | 0.200 | 0.051 | 0.211 |
| Household Income | 0.189 | -0.079 | 0.145 | -0.030 |
| Education | 0.000 | 0.000 | 0.000 | 0.000 |
| Internet Usage | 0.000 | 0.000 | 0.000 | 0.000 |
| Commute Distance | -0.084 | -0.075 | -0.097 | -0.087 |
| No. of Vehicles | 0.067 | 0.119 | 0.052 | 0.109 |
| Average Age of Drivers | 0.010 | 0.006 | 0.017 | -0.004 |
| Share of Female Drivers | -0.047 | 0.034 | -0.048 | 0.051 |
| Household Size | -0.023 | -0.004 | -0.035 | -0.006 |
| No. of Workers | -0.042 | -0.075 | -0.055 | -0.079 |
| No. of Drivers | -0.152 | 0.009 | -0.161 | -0.005 |
| Life Cycle | -0.138 | -0.003 | -0.129 | 0.003 |
| Race | -0.050 | -0.019 | -0.040 | 0.008 |
| Hispanic | -0.099 | -0.159 | -0.102 | -0.158 |
| Market Penetration Rate | -0.010 | -0.001 | -0.009 | -0.011 |
| Gas Price (Purchase) | -0.012 | -0.116 | -0.016 | -0.115 |
| Gas Price (Survey) | 0.003 | -0.001 | -0.003 | -0.001 |
| MSA Category | -0.010 | -0.022 | 0.000 | -0.015 |
| Rail in MSA | -0.005 | -0.001 | -0.009 | -0.002 |
| Urban | -0.133 | 0.113 | -0.126 | 0.119 |
| GPC Index | -0.025 | 0.030 | 0.014 | 0.039 |
| CBSA | 0.000 | 0.000 | 0.000 | 0.000 |

Post-match normalized difference and log ratio of standard deviation statistics for the matched estimates reported in Table 4. An exact match is required for household education, frequency of Internet usage, year of hybrid purchase, counterparts of hybrid, and CBSA. One-to-one nearest neighbor matches using the Mahalanobis distance metric was required for household income, size, vehicle count, MPG of other vehicles, commute distance, age, share of female, and GPC index. See the notes to Table 4 and text for further details.

**Table B4**: Post-match Balancing Assessment for Zip Code and Vehicle Type Matching Model – Hybrid Treatment

| Covariate | Normalized Difference | Log Diff. of Std. Dev. |
|---|---|---|
| Vehicle Type | 0.000 | 0.000 |
| Year Purchased | 0.000 | 0.000 |
| MPG of Other Vehicles | 0.198 | 0.129 |
| Household Income | -0.016 | -0.037 |
| Education | 0.000 | 0.000 |
| Internet Usage | 0.000 | 0.000 |
| Commute Distance | -0.086 | -0.011 |
| No. of Vehicles | 0.040 | 0.157 |
| Average Age of Drivers | 0.081 | -0.019 |
| Share of Female Drivers | -0.001 | -0.035 |
| Household Size | 0.032 | 0.035 |
| No. of Workers | -0.147 | 0.049 |
| No. of Drivers | -0.074 | -0.005 |
| Life Cycle | 0.181 | -0.010 |
| Race | -0.010 | 0.084 |
| Hispanic | -0.059 | -0.119 |
| Market Penetration Rate | -0.024 | -0.010 |
| Gas Price (Purchase) | -0.031 | 0.002 |
| Gas Price (Survey) | 0.000 | 0.000 |
| MSA Category | 0.000 | 0.000 |
| Rail in MSA | 0.000 | 0.000 |
| Urban | -0.115 | 0.084 |
| GPC Index | 0.000 | 0.000 |
| Zip Code | 0.000 | 0.000 |

Post-match normalized difference and log ratio of standard deviation statistics for the matched estimates reported in Table 4. An exact match is required for household education, frequency of Internet usage, year of hybrid purchase, vehicle type, and zip code. One-to-one nearest neighbor matches using the Mahalanobis distance metric was required for household income, size, vehicle count, MPG of other vehicles, commute distance, age, share of female, and GPC index. See the notes to Table 4 and text for further details.

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