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Implications for Miles Traveled and Gasoline Consumption

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Hybrid Vehicles and Household Driving Behavior: Implications for Miles Traveled and Gasoline Consumption

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Abstract

We estimate the impact of gasoline-electric hybrid vehicle ownership on annual miles traveled in order to understand the relationship between hybrid ownership and fuel consumption. When the higher fuel efficiency of hybrid vehicles is able to reduce gasoline consumption in driving, the lower driving cost (e.g., financial cost, environmental cost) of hybrids may lead to rebound effects of driving behavior, which could offset the reductions in gasoline consumption from hybrids vehicles. We measure two types of rebound effects associated with hybrid adoption. The first one is the total rebound effect, in which a hybrid owner drives more after adopting a hybrid vehicle. The second is a social status driven rebound effect, in which the owner of a visually distinct hybrid vehicle drives more to signal his/her environmental consciousness. We focus on issues of identification in light of observable and unobservable factors that influence both hybrid adoption and miles traveled, and develop a matching strategy to account for these factors that allows us to recover causal effects. Despite prior evidence of the status signaling effect of visually distinct hybrid vehicles, we do not find evidence of a statistically significant status-driven rebound effect. However, we find a total rebound effect on miles traveled of about 3 percent of the (average) annual miles traveled that only slightly offsets the reduction in fuel consumption from the higher fuel efficiency of hybrid vehicles. We calculate that hybrid adoption reduces fuel consumption by 34 to 46 percent per year compared to conventional gasoline powered vehicles.

JEL-classification: C21; Q42; Q48; Q53; Q55; Q58

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Keywords: Gasoline consumption; Hybrid vehicles; Miles traveled; Rebound effects; Treatment effects

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. Understanding the effect of hybrid ownership on gasoline consumption is not only important for evaluating policies directed toward hybrid adoption, but also for predicting the possible effects of subsequent policies focusing on other alternative-fuel vehicles.

The reduction in fuel consumption following hybrid adoption may be achieved through the intensive and extensive margins. On the intensive margin, hybrid adoption reduces gasoline consumption, *ceteris paribus*, because hybrids are more fuel efficient than conventional engine vehicles. On the extensive margin, an increase in the penetration rate of hybrid vehicles in the automobile market stimulates further, widespread adoption of hybrids which leads to a higher level of aggregate fuel saving. The extensive margin stimulation of widespread adoption depends, in part, on the extent to which households perceive the prevalence of hybrids in their communities. A hybrid that is visually distinct from other conventional engine vehicles – such as the Toyota Prius – is more easily noticed as a hybrid, and therefore better stimulates further adoption of hybrids relative to a hybrid that is less visually distinct.[3]

[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 June 11, 2015).

[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.

Theory predicts that an increase in fuel efficiency may lead to an increase in vehicle miles traveled because of the decrease in the cost of travel (Chan and Gillingham 2015). Since hybrids are more fuel efficient compared to their conventional engine counterparts, a household has an incentive to increase its miles traveled after adopting a hybrid. This effect is known as the rebound effect. In addition, recent work (e.g., Narayanan and Nair 2013, Sexton and Sexton 2014, Delgado et al. 2015) shows that environmental social status effects – i.e., the desire for a household to drive a hybrid to signal that he/she adheres to (local) biocentric social norms to maintain his/her relative standing among peers – is an important and statistically significant factor explaining the proliferation of the Toyota Prius.[4] Hence, the owner of a hybrid may have an additional incentive to drive more to send out a social status signal, and this incentive may be particularly strong for the owner of a visually distinct hybrid. This incentive creates a special rebound effect – a social status driven rebound effect, over and above the rebound effect traditionally associated with more fuel efficient vehicles.[5]

Therefore, for hybrid ownership to lead to a (large) reduction in fuel consumption, owning a hybrid should not cause a household to increase its driving miles to the extent that the reduction in fuel consumption due to the higher fuel efficiency of the hybrid is substantially offset. That is, the total rebound effect – the aggregate of the traditional rebound effect and the social status driven rebound effect – associated with hybrid adoption should not be sufficiently large. In addition, for the visually distinctive hybrids to induce further reduction of fuel consumption through stimulating the hybrid vehicle market, the visual distinctiveness of these hybrids do not lead to a substantial social status driven rebound effect.

We examine the existence and size of these two hybrid vehicle rebound effects. To measure the total rebound effect, we consider hybrid ownership as a treatment and

[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.

estimate the treatment effect as the difference in annual miles traveled by hybrid household and their non-hybrid counterparts. To measure the social status driven rebound effect, we model the 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. As our objective is to explore the causal 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.

If hybrid ownership was randomly distributed throughout the population, we could compare the average gasoline consumption of hybrid-owning households and non-hybrid-owning households to ascertain whether a policy that encourages hybrid ownership generates a significant reduction in gasoline consumption. However, hybrid ownership is not random: households that purchase hybrids usually have greater motivation to reduce travel costs, or have stronger preferences for biocentrism, egoism, and/or social status. Similarly, households that purchase the Toyota Prius may face different incentives or have different preferences compared to households that purchase non-Prius hybrids. In other words, households self-select into hybrid and/or Prius ownership, and this self-selection must be accounted for when estimating the causal effect of hybrid (Prius) adoption on annual vehicle miles traveled and fuel consumption. One contribution of this paper is that we design an empirical strategy that directly deals with the non-randomness of hybrid (Prius) ownership.

Our empirical strategy centers on a 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 the potential for bias stemming from such observable factors.

We remain concerned, however, that there are three factors that could substantially affect both hybrid (Prius) adoption and vehicle miles traveled, but are difficult to observe. These factors include: 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. Econometrically, ignoring these factors may lead to an omitted variable bias. An instrumental variables approach is commonly used to solve the omitted variables problem, but in our case it is difficult to find an instrumental variable that is both valid and relevant (see section 3.2.4 for details). Instead, we pursue a different strategy that exploits both the richness of our data and the flexibility of the matching estimator. We eliminate the possibility of bias coming from unobservable local social norms by requiring an exact geographical match between treated and untreated households at the CBSA or zip code level.[6] We eliminate the possibility of bias coming from differences in household preferences for lower travel cost and environmental preservation by conducting a nearest neighbor match on the average fuel efficiency rating of other vehicles owned by the household – other than the one defining the hybrid (Prius) status of the household. A household (that owns multiple vehicles) that has greater preference for lower travel cost and/or environmental preservation is more likely to have a higher average fuel efficiency rating on all non-hybrid vehicles it owns. The result of our matching strategy is that each matched 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.

Our analysis is the first to directly investigate hybrid-specific rebound effects in terms of driving distance and gasoline consumption. A large number of studies (e.g., Greene 1992, Jones 1993, Haughton and Sarkar 1996, Goldberg 1998, Greene et al. 1999, Pickrell and Schimek 1999, West 2004, Small and Van Dender 2007, Hymel et al. 2010, Barla et al. 2009, Wang et al. 2012, Gillingham 2011, Greene 2012, De Borger et al. 2016) investigate rebound effects associated with a general increase in vehicle fuel efficiency in terms of driving distance or fuel consumption, but they do not focus on

[6] There is precedence in defining social norms at the city or community level in related empirical work. Examples include Kahn (2007) and Sexton and Sexton (2015).

hybrid vehicles. Hybrid vehicles denote a significant jump in fuel efficiency, even compared to conventional vehicles that are fuel efficient; hybrids are also associated with the special signaling value of social norms, especially for visually distinct gasoline-hybrids like the Toyota Prius. Therefore, it remains to be seen whether the rebound effects for hybrid vehicles are substantially different from rebound effects for fuel-efficient, conventional engine vehicles. Furthermore, we are the first to investigate the social status rebound effect.

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; 1,356 of them are hybrid vehicles; 726 of hybrids are Toyota Priuses[7]. 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 associated with the adoption of visually distinct hybrids. That is, while the special social signaling value of a visually distinct hybrid is capitalized in its market price (Delgado et al 2015) , this visual distinctiveness does not induce an extra rebound effect – for a driver of a visually distinct hybrid, the marginal benefit of social status derived from additional driving does not outweigh the marginal cost of additional driving (i.e., the monetary costs and non-monetary opportunity costs). However, we find that, overall, hybrid adoption causes an average household to drive more miles per year compared to a non-hybrid counterfactual household.his 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. These estimates indicate that hybrid vehicle adoption generates substantial reduction in fuel consumption, on the order of 34-46 percent per year.

[7] Some households have more than one hybrid or Toyota Prius.

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. Such evidence motivates our position that hybrid ownership is not random in the population of consumers. 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.[8] 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

[8] 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.

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

The literature on the rebound effect focuses on general improvements in fuel efficiency, and not hybrid adoption specifically. Some of the earlier studies use aggregated 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 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 of 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 two and other previous studies, this study has two main contributions. First, we focus on two rebound effects associated with hybrid vehicles: the social status rebound effect and the total rebound effect which, in our case, includes the rebound effect due to social status and the rebound effect due to the higher fuel efficiency of gasoline electric hybrid vehicles. As far as we know, the social status rebound effect has yet to be empirically investigated. 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) describe how regression estimates of causal parameters can be sensitive to imbalance in the covariates; as we

show, such imbalance 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 control for certain types of unobservable factors that are known to influence driving habits and hybrid adoption. 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 are significant.

3 Model, Identification, and Estimation

3.1 Empirical Propositions

Proposition 1 *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.

Proposition 2 *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 certain hybrids and related findings from previous research. 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, we restrict the sample to only hybrid households and define Prius ownership as treatment to estimate the social status rebound effect.

3.2 Empirical Framework

3.2.1 Econometric Model

We imagine two potential outcomes:

$$Y_{1i} = \mu_1(X_i) + U_{1i}$$
$$Y_{0i} = \mu_0(X_i) + U_{0i} \quad (1)$$

in which Y_{ji} is the total annual vehicle miles traveled by household $i = 1, 2, \dots, n$ 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, $\mu_j(X_i)$: $\mathbb{R}^k \rightarrow \mathbb{R}$ 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, hybrid treatment and Prius treatment, as whether or not a household owns a gasoline-electric hybrid or Prius, respectively. For hybrid treatment, any household that has purchased at least one brand new hybrid vehicle in the 2000s decade is considered treated, and any household that has purchased at least one brand new non-hybrid vehicle during the same period and does not own any hybrid

vehicle is part of the control group.[9] For Prius treatment, any household that has purchased a brand new Prius is considered treated, and any household that purchased a brand new non-Prius hybrid is part of the control group.

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 (τ_{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.[10]

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-

[9] 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. 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.

[10] Our probit estimates of the propensity score (reported in the 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 many probit models we estimate we do not obtain estimates of the propensity score for the hybrid model that have a maximum support that exceeds about 0.55. In all models, we find estimates of the propensity score arbitrarily close to zero, which indicates that the ATT is identified. These results are intuitive. A stereotypical hybrid household in our data has relatively high income and high education. It is easy to find non-hybrid households that match the same demographic characteristics, which means that comparison of households on the basis of observable demographics does not have sufficient power to satisfy the full support condition.

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, for each household that has purchased a brand new hybrid (Prius) vehicle, we find a household that has purchased a brand new non-hybrid vehicle (non-Prius hybrid) to match. 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). The purchased brand new vehicle in each household plays an important role in our analysis. We use the purchase of only one such vehicle to define the treatment status of the household. For non-hybrid 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 households, the purchase of a brand new hybrid is chosen; 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.

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 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, but may also have greater incentive to drive the hybrid 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 an observable indicator, the average fuel efficiency rating of all other vehicles 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 a more fuel efficient vehicle, 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 simultaneously influence the measure of household preference on lower travel cost and environmental preservation and treatment status, 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 environmentalists 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 impossible 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 hybrid was purchased. As discussed earlier, the market penetration rate, gasoline prices, and federal policy incentives, which vary temporally, are important factors affecting hybrid adoption. By requiring a hybrid household to match to a non-hybrid household that purchased a vehicle in the same year, we eliminate the effects of such time varying observable factors on hybrid 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 household in San Francisco to be matched to a non-hybrid 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 model. An exact match on vehicle type ensures that a hybrid household is matched to a non-hybrid household that purchased a similar sized vehicle (i.e., a vehicle in the same class). To strengthen this matching dimension, we also consider models that exactly match 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 ensure that matched households are similar in vehicle tastes and preferences, with the only difference being whether or not the vehicle is a hybrid.

Other dimensions over which we conduct exact matching include 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 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 all 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 as well.

We deploy the same matching strategy for Prius treatment, except that we conduct nearest neighbor matching on education instead of requiring an exact match since the exact match on education no longer improves the post-match balance for the model of Prius treatment.

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.[11] However, our preliminary regressions strongly indicate that the effects of these variables on hybrid adoption are weak and unreliable when using household data. The weakness of these instruments comes from the 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 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

[11] 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 even less reliable than the federal incentive measures.

standard errors, and does not pass standard tests of weak instruments.[12]

Moreover, hybrid 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 hybrid 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 an instrumental variables approach 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.

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

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

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. To eliminate 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.

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.

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.[13] 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 Supplemental Appendix 1.2 describes these variables in detail, so that our discussion here focuses exclusively on the variables we directly include in our set of matching covariates.

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 education level of the household member with the highest level of education in the household to capture the highest 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

[13] 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.

	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	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. Table A4 in the Supplemental Appendix provides the sample distribution of all hybrid makes and models. The Toyota Prius is the most popular hybrid model, contributing to over 50 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 (hybrid versus non-hybrid households, and Prius-hybrid households versus non-Prius-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, σ^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 σ 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. Formally, we calculate this percentage via

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

$$\pi_0^{\alpha} = \left[1 - F_0\left(F_1^{-1}(1 - \alpha/2)\right)\right] + F_0\left(F_1^{-1}(\alpha/2)\right) \quad (7)$$

for significance level $\alpha = 0.05$ and distribution functions $F(\cdot)$.

5.2 Pre-Match Assessment of Balance and Overlap

We report the results for our pre-match balance and overlap assessments in the Supplemental Appendix Table A7-A8. 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. 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.

There are 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 these covariates between hybrid and non-hybrid samples.[14] The overlap comes from the large number of non-hybrid (control) households in the NHTS survey.

For the sample corresponding to the Prius treatment model, there are fewer

[14] 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 few countable bins.

significant differences between Prius and non-Prius hybrid samples pre-match. The largest 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.

5.3 The Effect of Hybrid Ownership on Annual Miles Traveled

Our matching estimates of the effect of hybrid ownership on annual miles traveled are reported in Table 3. 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. The bottom panel restricts the exact match to the zip code level; because of limitations in the data when matching at the zip code level, we only further restrict the exact match to vehicle type, not to the conventional engine counterpart. The rest of the matching is as described previously, in which education, 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, while Model 2 eliminates these households.

Each model specification has its own strength. 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 view the combination of these models as complementary.

We find that in most of the models we estimate, hybrid-ownership causes households to drive more miles per year than households that do not own a hybrid. Our estimates of the causal effect range from just under 400 miles per year to just over 785. 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, and has the same (or at least very similar) preferences on lower travel cost and/or environmental preservation and household demographics. The only insignificant rebound effect comes from the model matching on CBSA, non-hybrid counterparts, and excluding households not in a CBSA.

Table 3: 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.

5.4 Is There A Social Status Rebound Effect?

We report our matching estimates of the *ATT* for the social status driven rebound effect in Table 4 for the two CBSA models that match on vehicle type. Due to the relatively small sample size of the hybrid households, we are not able to conduct matching at the zip code level. 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, though visually distinctive hybrid vehicles better stimulate widespread adoption of hybrids (which, *ceteris paribus*, leads to further reduction in fuel consumption in the future), this visual distinctiveness does not induce any increase in miles traveled and fuel consumption. The intuition is straightforward: the marginal benefit of additional social status earned from driving the visually distinct hybrid additional miles does not outweigh the associated marginal costs, which may be monetary and non-monetary opportunity costs.

Table 4: 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.

5.5 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 the Supplemental Appendix (Table A9-A12). 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 (Appendix Figure A1) 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. It indicates that when we balance this covariate in certain models, even though the prefect balance is not reached in other models, there is little chance that this variable causes bias in our estimates.

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 simple means of adjusting for observable covariates within the matched sample, and it is important to use the matched sample for this adjustment because the unmatched sample is too imbalanced to reliably estimate a linear regression (see Imbens and Rubin 2015). We continue to find that Prius treatment is not significant (see the appendix Table A13).

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:

$$Proportional\ reduction\ in\ fuel\ consumption = 1 - \frac{(1 + \Delta\, VMT/VMT_{non})}{(1 + \Delta\, MPG/MPG_{non})} \quad (8)$$

where ΔVMT is the change in vehicle miles traveled following hybrid adoption, ΔMPG 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 3, and the increase in fuel efficiency is calculated based on the difference in fuel efficiency between hybrid and non-hybrid vehicles that define the treatment status of households. 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 3 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 3. 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 considering 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 which falls into the same vehicle type of a certain hybrid will otherwise purchase a hybrid (after considering all other influencing factors).

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 3, 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 3, 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.[15] 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 households drive more due to hybrid adoption, and whether there is a significant social status driven rebound effect associated with visually distinctive hybrids. 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

[15] 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.

economy.

We find a statistically significant causal rebound effect due to the adoption of a hybrid: 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. Additionally, we do not find any evidence of a statistically significant social status rebound effect associated with ownership of visually distinctive hybrid vehicles. 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.

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