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Behavioral responses and policy evaluation: Revisiting water and fuel policies

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BEHAVIORAL RESPONSES AND POLICY EVALUATION:

REVISITING WATER AND FUEL POLICIES

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To my daughter, Yangchen

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It is hard to believe that it has already been five years since I began my PhD program at Purdue in the autumn of 2011. These past five years have been the quickest and most enjoyable five years of my life. Every class I took, every project I worked on, every conference I attended, every presentation I made, and, even, every night I worked late became a pleasant memory which I will own forever. This dissertation is the culmination of all the enjoyable work which I have completed over these five years, and it has become one of the most valuable things in my life.

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ABSTRACT

Sun, Shanxia PhD, Purdue University, May 2016. Behavioral Responses and Policy Evaluation: Revisiting Water and Fuel Policies. Major Professors: Juan P. Sesmero and Michael S. Delgado.

In my dissertation, I examine how policies regulating agricultural production and clean technology impact the environment. I focus on policies affecting water depletion, water pollution, and fuel consumption. I assess their cost-effectiveness by modeling and quantifying the behavioral responses of farmers and households.

My first essay focuses on decreasing groundwater depletion through increasing irrigation efficiency in Mexico. I quantify the impacts of different sources of inefficiency on groundwater extraction, and I evaluate the effectiveness of alternative policies that aim to reduce the over-extraction of groundwater. I find that mechanisms of electricity cost-sharing implemented in many wells have a sizable impact on the inefficiency of irrigation applications; thus, policies eliminating electricity cost-sharing mechanisms have a substantial effect on decreasing groundwater depletion. In contrast, price-based policies are less effective, and policies targeting well-sharing do not have significant effect on reducing irrigation application and groundwater depletion.

In my second essay, I assess policies which attempt to reduce water pollution by reducing fertilizer application. Input- and output-based economic policies designed to reduce water pollution from fertilizer runoff by adjusting management practices are theoretically justified and well-understood. Yet, in practice, adjustment in fertilizer application or land allocation may be sluggish. I incorporate time cost as a new dimension in the assessment of these policies and simultaneously quantify the magnitude

of the policy effectiveness and the speed at which the policies take effect. I find that while both input- and output-based policies are able to induce a significant reduction in fertilizer application, input-based policies are more cost-effective than their output-based counterparts. Further, input- and output-based policies yield adjustment in fertilizer application at the same speed, and most of the adjustment takes place in the short-term. Due to the rapid adjustment in land allocation between corn and soybeans, the long-term effects of the policies can also be rapidly achieved. Though the time cost does not constitute a major concern in my research area, the time dimension may be important in research areas in which there are different crops that may not be easily substituted between.

In my third essay, I explore household adoption of gasoline-electric hybrid vehicles and the impact of hybrid ownership on annual miles traveled in order to understand how hybrid ownership impacts fuel savings. I focus on issues of identification in light of several behavioral factors that are believed to influence both hybrid adoption and miles traveled. I measure two types of rebound effects associated with hybrid adoption. The first one is a traditional rebound effect in which a hybrid owner drives more due to the lower travel cost from higher fuel efficiency; the second one is a social status driven rebound effect in which a hybrid owner drives more to signal his environmental friendliness through driving a hybrid. I find a statistically significant traditional rebound effect on miles traveled. However, this rebound effect is only 3% of the average annual miles traveled and only slightly offsets the fuel savings from the higher fuel efficiency of the hybrid. I do not find evidence of a status-driven rebound effect. I estimate that hybrid adoption induces substantial fuel savings that amount to about half of the average fuel consumption of regular vehicles.

CHAPTER 1 INTRODUCTION

Water, fuel, and air are critical in many ways for human and natural systems. Water and fuel are important inputs in numerous production and service systems (e.g., agriculture, industry, transportation). Water and air are essential elements that sustain life, balance ecological systems, and create a pleasant environment.

Like all natural resources, water and fuel are not unlimited. According to the report of Gleick and Ajami (2014), there are 3.3 billion people in the world living in the areas with physical water scarcity, approaching physical scarcity, or economic water scarcity. The supply of fuel is limited by the total natural reserves of oil and the ability of current technology to exploit those reserves. The demand for energy increases with increases in the population and with economic development; the increased demand and limited supply can lead to sharp increases in prices (e.g., 2000s Energy Crisis). The scarcity of water and fuel points to the importance of increasing efficiency in the use of water and fuel.

As part of the environment, water and air face continuous degradation caused by pollution from economic production and human life. Water pollution is a serious problem in both developed and developing countries. According to a report from the United Nations, “Water quality is becoming a global concern of increasing significance, as risks of degradation translate directly into social economic impacts” (UN 2012). The severity of air pollution is already widely acknowledged. A recent report from the World Health Organisation (WHO) states that air pollution exposure caused the death of around 7 million people in 2012 (WHO 2014). The severity of these issues points toward the importance of controlling the pollution of water and air from economic production and human life.

1.1 Water and Agriculture

Water is an essential factor in many production systems. The major use of water is agriculture, which makes up 70 percent of total freshwater use (Gleick and Ajami 2014). In particular, I focus on the interface between water and agriculture in terms of both water use and water quality.

1.1.1 Efficiency in Water Use

My first essay focuses on quantitative evaluation of factors influencing irrigation efficiency in Mexico. Such evaluation allows me to identify policies which most effectively increase irrigation efficiency and alleviate groundwater depletion from over-extraction of groundwater. As an arid and semi-arid country, Mexico's groundwater resources are being depleted; in some areas, the depletion is severe. The Mexican federal government subsidizes the electricity used in pumping groundwater, which creates an incentive to extract. Other potential drivers of over-pumping in Mexico are that wells are commonly shared by several farmers and moreover, in some shared wells the total cost of electricity is distributed among all irrigators. Sharing wells may aggravate externalities associated with exploitation of a common access resource and increase pumping beyond the efficient level. Sharing electricity costs reduces the marginal cost of water pumping since all farmers sharing the bill jointly pay for the cost of additional pumping from one farmer. Subsidies and institutions that decrease the marginal cost of groundwater consumption may exacerbate the over-exploitation of groundwater and aggravate groundwater depletion. Quantification of the main causes of over-extraction of groundwater by farmers has important policy implications.

The objective of my first essay is threefold. First, I estimate water demand, including the potential for allocative inefficiency. Allowing for inefficiency in the estimation of irrigation water demand results in a more reliable elasticity estimate (Kumbhakar 2001). Second, I estimate the inefficiency in agricultural irrigation in Mexico. Finally, I quantify the role of different sources of externalities (i.e., cost-sharing rules and the extent to which groundwater resources are non-excludable) behind systematic inefficiency.

1.1.2 Reducing Water Pollution from Agriculture

My second essay focuses on the assessment of policies that aim to decrease water pollution from agriculture. Water pollution can threaten human health and the stability of ecosystems. Also, some polluted water may become unsuitable for consumption aggravating water scarcity. Hence mitigating water pollution may be a vehicle to address water quantity as well as water quality issues. Fertilizer use in agriculture is a significant source of nonpoint source pollution to water (Rabotyagov et al. 2010; Yuan et al. 2013; Rebolledo et al. 2016). As a country with a highly developed agricultural system the United States faces severe water pollution from agriculture. Finding the most cost-effective policies to alleviate this problem is a concern of policymakers who are interested in both the overall effect of the policy and the speed of effectiveness. Assessing the cost-effectiveness of policies mitigating agricultural water pollution through decreasing fertilizer use in agricultural production is my main objective.

Many policies attempt to reduce water pollution by reducing fertilizer application in agriculture, which could be realized by decreasing the fertilizer application rate on a certain area or switching land allocation from fertilizer-intensive crops to fertilizer-saving crops. While the adjustment of the fertilizer application rate in a certain area can be rapid, adjustments to land allocation across crops may be restricted by crop rotational effects and quasi-fixed capital constraints (Orazem and Miranowski 1994; Arnberg and Hansen 2012) and require a long time to be fully realized. For policymakers, not only the magnitude of policy effectiveness but also the speed at which policies take effect are key concerns when they select the most suitable policy. I quantify both dimensions in the policy assessments in my second essay.

1.2 Fuel Consumption from Household Transportation

The world transportation sector accounts for almost half the world oil consumption, and was responsible for 23 percent of world energy-related GHG emissions in 2004. Three quarters of the emissions come from road vehicles (Kahn Ribeiro et al. 2007). In the United States, the transportation sector is also one of the largest contributors to U.S.

GHG emissions, being responsible for 28 percent of total U.S. GHG emissions in 2012 (US EPA 2015).

Given the pressures faced by the transportation sector, the United States government has designed the Corporate Average Fuel Economy (CAFE) standards to improve the average fuel economy of cars and light trucks sold in the United States. In part to meet the CAFE criterion the federal government (and some state and local government) has provided many incentives to encourage the adoption of fuel-efficient vehicles. The gasoline-electric hybrid has been the focus of many policies, as conventional wisdom suggests that a driver of a hybrid will consume less gasoline than had he/she driven a conventional engine vehicle.

However, a rebound effect is often associated with the adoption of more efficient technology, given the reality that higher efficiency means lower cost of use. In the case of hybrid adoption, it means that the higher fuel-efficiency of a hybrid vehicle reduces the cost of travel, which consequently may increase the driving miles of a household. It is important to understand the extent to which the rebound effects offset the impact from higher fuel efficiency, in order to understand the true potential for hybrid adoption to reduce gasoline consumption. In another words, it is crucial to examine the existence and magnitude of any rebound effects of hybrid adoption. The objective of my third essay is to understand whether there are rebound effects associated with the adoption of hybrid vehicles, and what the magnitudes of the rebound effects are if they exist.

My analysis focuses on two types of rebound effects. The first one is a traditional rebound effect in which a hybrid owner drives more due to the lower travel cost from higher fuel efficiency of the hybrid. The second one, that has yet to be discussed in the literature, is a social status driven rebound effect. Sexton and Sexton (2014) and Delgado et al. (2015) find that social status incentives are a significant factor underlying consumer demand for the Toyota Prius. I hypothesize that this same social status incentive leads hybrid owners to increase miles traveled. This hypothesis rests on two facts: first, the most popular hybrid over the 2000's decade was the Prius, easily identified by its unique body trim; and second, a consumer interested in signaling his/her environmental preferences via vehicle ownership is better able to do so through increased driving exposure.

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CHAPTER 2 THE ROLE OF COMMON POOL PROBLEMS IN IRRIGATION INEFFICIENCY: A CASE STUDY IN GROUNDWATER PUMPING IN MEXICO

2.1 Introduction

It is well known that the economically efficient use of finite natural resources requires those resources to be priced at the marginal social cost which includes externalities associated with extraction. When prices do not reflect the full social cost it is expected that resource use exceeds a socially optimal level. One such resource is groundwater; groundwater aquifers can be either renewable or non-renewable but are always finite. Policies to reduce over-extraction such as a per-unit tax on groundwater extraction (Shah et al. 1993; Howe 2002) or creating property rights (Provencher and Burt 1994) may be difficult to implement. Consequently it is important to examine alternative policy instruments that can successfully tackle the depletion problem.

Groundwater use accounts for approximately 26 percent of all water use worldwide and is a source of almost half of all irrigation water (van der Gun 2012). Price-distorting policies such as subsidized electricity rates may lead to excessive extraction and exacerbate groundwater depletion (Schoengold and Zilberman 2007). Subsidized electricity or diesel rates for irrigators are pervasive in many countries including India, Mexico, Jordan, and Syria (Scott and Shah 2004; Shah et al. 2007).

In addition to subsidized pumping costs it is also common in developing countries for multiple irrigators to share a single well (see Huang et al. 2013 for a discussion of this issue in China; the current study evaluates Mexico's shared wells). This situation may exacerbate over-extraction due to strategic behavior by farmers (Provencher and Burt 1993). Moreover, in some communal wells, the cost of energy associated with pumping is shared by irrigators using the well due to inadequate metering systems. Rules for cost-sharing may be based on parameters that are indirect measures of water use such as land holdings, or may be based on an arbitrary rule such as equal cost-sharing. These rules introduce further distortions between what the farmer pays and the actual cost of pumping and cause inefficiency in irrigation.

The objective of this study is threefold. First, we will estimate water demand, including the potential for allocative inefficiency. Allowing for inefficiency in the estimation of irrigation water demand results in a more reliable elasticity estimate (Kumbhakar 2001). Second, we will gauge the inefficiency (if any exist) with which irrigation is applied by farmers in Mexico. Finally we will quantify the role of different sources of externalities (i.e., cost-sharing rules and the extent to which groundwater resources are non-excludable) behind systematic inefficiency. Quantification of the main causes of over-extraction of groundwater by farmers has important policy implications. If institutional arrangements creating common pool problems are the main cause, as opposed to subsidies in electricity price, institutional reforms will constitute a viable mechanism for water conservation. If pumping is sensitive to the cost of electricity, removal of subsidies can have a sizable impact on groundwater extraction.

The paper is organized as follows. First, we review the existing literature. Second, we model key features of electricity subsidies, well-sharing, and cost-sharing, and identify their distortions to the marginal cost of pumping. Third, we describe the empirical model and data used to estimate water demand and farmers' irrigation efficiency. The final sections report estimation results, and discuss policy implications and conclusions.

2.2 Review of Literature

It has been established theoretically that non-excludability of groundwater resources may result in over-application of irrigation. This is because non-excludability causes a cost externality (Gisser and Sanchez 1980; Negri 1989) and a strategic externality (Negri 1989; Provencher and Burt 1993; Rubio and Casino 2001, 2003), both of which tend to reduce private marginal cost of pumping relative to the social marginal cost and increase irrigation application. Subsequent empirical analyses uncovered evidence supporting these theoretical predictions (Pfeiffer and Lin 2012; Huang et al. 2013).

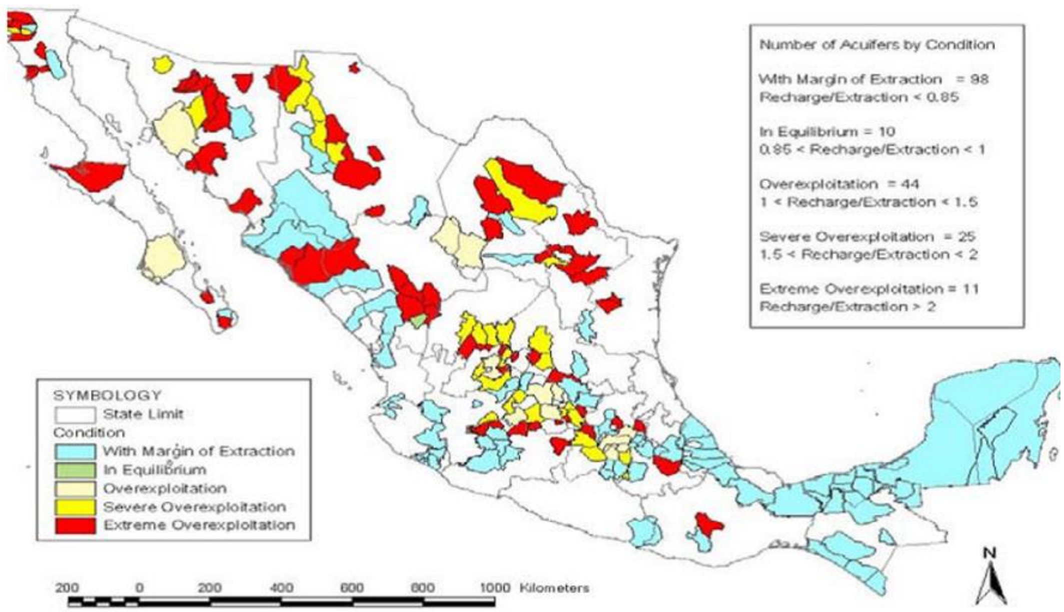
Substantial research has focused on the estimation of irrigation water demand (Ogg and Gollehon 1989; Schoengold et al. 2006; Huang et al. 2010; Hendricks and Peterson 2012) but this research assumes that farmers use water efficiently. The assumption of efficiency may constitute a source of bias in estimation of demand elasticity (Kumbhakar 2001). Moreover this assumption implies attributing over-extraction to random factors precluding quantification of systematic sources behind it.

Despite sound theoretical reasons to suspect inefficiencies in irrigation application, very few studies have quantified this inefficiency and explored their reasons. McGuckin, et al. (1992) was the first study to estimate the sources of inefficiency in irrigation water use among corn producers in Nebraska, United States, based on a stochastic production frontier function. Karagiannis et al. (2003) estimate efficiency in irrigation practices for out-of-season vegetable cultivation in Greece. Finally, Dhehibi et al. (2007) gauge both technical and irrigation water efficiency in Tunisia. Unfortunately, these studies have not estimated a demand for irrigation water precluding comparison between price-based policies and other types of policies.

This study uses a stochastic frontier for estimation of irrigation efficiency and its sources but in contrast to previous studies we use a method first developed by Kumbhakar (1989) that allows measurement of input-specific allocative efficiency based on a cost frontier. Using a dual measure of efficiency allows estimation of derived demands. This is critical in this context as we are also interested in estimation of price elasticity of irrigation water demand so that price-based and institutions-based policies can be compared.

2.3 Groundwater Depletion in Mexico: Background

Mexico is classified as an arid and semi-arid country. Therefore irrigation constitutes a critical input to agricultural production in many regions of the country. According to information from the Food and Agricultural Organization (FAO), about a quarter of total land area in Mexico is equipped for irrigated agriculture and about half of the total value of agricultural production is produced under irrigation. Moreover, about a third of irrigated land in Mexico uses groundwater and the rest is irrigated with surface water.



Source: Comisión Nacional del Agua (National Water Commission), Mexico

Figure 2.1: Aquifer Depletion in Mexico

In 2006, preliminary evaluations of the situation in Mexico were conducted with the purpose of informing the Mexican government’s national hydrological program. The resulting report (Programa Nacional Hidrico 2007-2012) asserted that, among other causes, inefficiencies in the use of water had caused overexploitation of groundwater reserves (Figure 2.1). It was further noted that electricity subsidies provided by the federal government could also be contributing to overexploitation of groundwater. One implication of this observation is that elimination of the electricity subsidy could help mitigate the depletion problem. But in addition to subsidies, well-sharing and electricity cost-sharing may also be partly responsible for inefficiency in water use. Therefore policymakers may also tackle over-extraction by reforming the institutions under which irrigators operate. Though mentioned in Programa Nacional Hidrico 2007-2012, an empirical quantification of distortionary forces behind over-extraction and the resulting potential of alternative policies, has not yet been conducted. This study attempts to fill that informational gap.

2.4 Distortions to Marginal Cost of Pumping

Mexican farmers do not pay for groundwater, only for the electricity used in pumping groundwater. Therefore the cost paid by the farmer per unit of water consumed depends on the amount of electricity used per unit of water pumped and the price of electricity. The amount of electricity used per unit of extracted groundwater (measured as kilowatts hour per cubic meter) is assumed to be a linear function of the depth to water table denoted by H; $\text{i.e.}, \frac{kwh}{m^3} = \alpha + \beta H$. Parameter β is positive as greater depth is associated with greater electricity consumption. Parameter α is also positive as the pump needs to be run even if distance to groundwater is zero ($H = 0$). We assume that total water extracted in a given period positively affects depth to the water table $H = \mu + \sum_i \varepsilon_i w_i$; where parameter μ captures depth to water table in the previous period plus recharge rate, w_i represents the i^{th} farmer's pumping rate, and ε_i is the effect of the farmer i's pumping on water level.

We begin by considering a case where water resources are perfectly excludable which serves as a benchmark for this analysis. Thus, since $\varepsilon_j = 0$ for all $j \neq i$, the unit cost of water for farmer i is:

$$P_i^w = p^{kwh}(a + bw_i) \tag{2.1}$$

where P_i^w denotes unit cost of water, p^{kwh} is the price of electricity per kilowatt hour, $\frac{kwh}{m^3}$ has been replaced by $(a + bw_i)$ (after plugging H into this expression) with $a = \alpha + \beta\mu$, $b = \beta\varepsilon_i$, and the rest is as defined before. The total cost of pumping can be denoted by:

$$TC_i^w = p^{kwh}(a + bw_i)w_i. \tag{2.2}$$

Based on total cost (2.2), marginal cost (partial derivative of total cost with respect to pumping rate) is depicted by:

$$MC_i^w = p^{kwh}(a + 2bw_i) \ . \tag{2.3}$$

This expression for marginal cost will be used as a benchmark against which marginal cost of pumping with policy or institutional distortions can be compared.

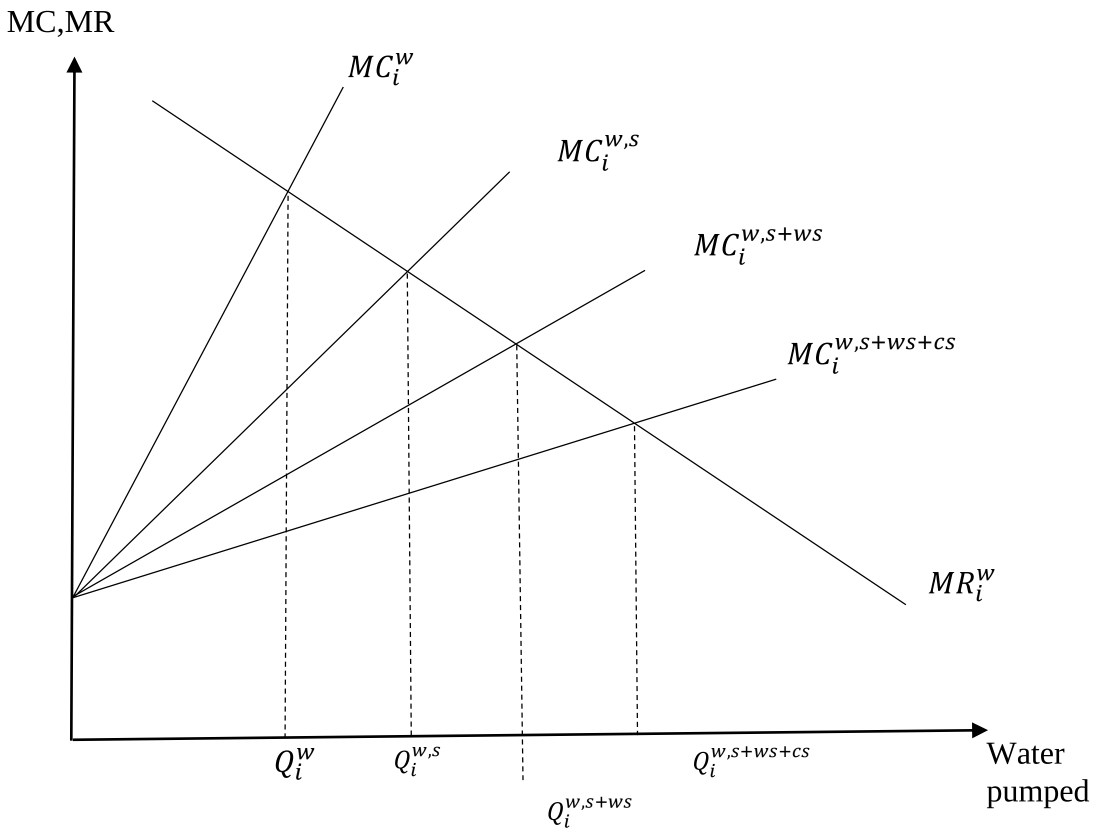


Figure 2.2: Sources of Distortions in Marginal Cost of Pumping

2.4.1 Electricity Subsidies

The federal government in Mexico subsidizes electricity used in pumping groundwater. Guevara-Sanginés (2006) estimates that the total subsidy to Mexican groundwater irrigators is approximately $700 million dollars per year.[1] An electricity subsidy operates as a reduction in the price per kilowatt hour of electricity paid by

[1] Estimates are in 2004 US dollars.

farmers. Therefore, under an electricity subsidy, the marginal cost of pumping groundwater is denoted by:

$$MC_i^{w,s} = [p^{kwh} - v^{kwh}] \quad (2.4)$$

where v^{kwh} represents the subsidy paid by the government per kilowatt hour of electricity consumed by the farmer, and the superscript s indicates electricity subsidy.

The reduction in marginal cost of pumping caused by the subsidy on electricity is illustrated in Figure 1 by a clockwise rotation of the marginal cost curve from MC_i^w to $MC_i^{w,s}$. Figure 1 also depicts a decreasing marginal revenue curve due to decreasing marginal productivity of irrigation. The combination of a clockwise rotation of marginal cost and a downward sloping marginal revenue curve causes an increase in pumping. The overall effect of the electricity subsidy on pumping will be determined by the magnitude of the subsidy and the marginal productivity of irrigation beyond Q_i^w.

2.4.2 Sharing of Wells among Farmers

The description of marginal cost of pumping in the previous section assumed a well is operated by a single farmer. However, different wells in Mexico function under different institutional arrangements. Some wells are individually owned while others are shared by multiple farmers. Table 2.1 describes the percentage of wells that are either owned by a single producer or jointly shared by multiple producers. As expected, we observe a large number of wells that are shared by multiple irrigators.

Models formalizing cost and strategic externalities (Provencher and Burt 1993) show that sharing of water resources by multiple irrigators may decrease marginal cost and aggravate over-extraction. Moreover these analyses have demonstrated that an increased number of irrigators sharing the resource is associated with greater pumping. As revealed by Table 2.1 the majority of wells (61 percent) are shared by multiple irrigators. Table 2.1 also shows the distribution of the number of users per well in our sample. The mean number of users is about 12. While the median size of the group is 6, about a quarter of wells are shared by more than 16 farmers. These figures suggest that inefficiencies or over-extraction due well sharing may be quantitatively relevant for Mexico’s aquifers.

Table 2.1: Distribution of Number of Users for Multi-producer Wells

Number of Users	Frequency	Percentage
1	77	39.1%
2 – 5	21	10.7%
6 – 10	35	17.8%
11 - 15	14	7.1%
16 - 20	13	6.6%
21 - 30	13	6.6%
31 - 40	13	6.6%
41 - 50	4	2.0%
51 - 75	5	2.5%
76 - 100	2	1.0%
Total	**197**	**100%**

When multiple farmers share a well, the depth of the water table is influenced by the sum of individual pumping rates. Moreover each farmer's pumping has the same effect on the depth to the water table such that $H = \mu + \sum_i \varepsilon w_i$; where w_i represents the i^{th}farmer's pumping rate, ε is the increase in depth per unit of water pumped, and the rest is as before. Thus, the unit cost of water for farmer i who shares a well with other farmers is:

$$P_i^{w,s+ws} = [p^{kwh} - v^{kwh}](a + b(w_i + \textstyle\sum_{j \neq i} w_j)) \tag{2.5}$$

where $P_i^{w,s+ws}$ denotes unit cost of water under an electricity subsidy and well-sharing, with ws in the superscript indicating well sharing, and the rest is as defined before.

Based on (2.5), marginal cost can be expressed as:

$$MC_i^{w,s+ws} = [p^{kwh} - v^{kwh}]((a + bW) + bw_i(1 + \rho)) \tag{2.6}$$

where $MC_i^{w,s+ws}$ denotes marginal pumping cost of water under an electricity subsidy and well-sharing; $W = \sum_{i=1}^{N} w_i = w_i + \sum_{j \neq i} w_j$; ρ is a parameter representing farmer i's conjecture about others' reactions to her pumping decisions; $\rho = \sum_{j \neq i} \frac{\partial w_j}{\partial w_i}$. This parameter typically captures the degree to which pumping rates by different farmers are strategic substitutes $\rho < 0$ or strategic complements $\rho > 0$. The parameter ρ is typically considered to range between 1 and -1.

The effect of both distortions (electricity subsidy and well-sharing) combined is captured in Figure 1 by a clockwise rotation of marginal cost of pumping from MC_i^w to $MC_i^{w,s+ws}$. The specific distortionary effect of well-sharing is depicted as the wedge between $MC_i^{w,s}$ and $MC_i^{w,s+ws}$. The magnitude of the increase in pumping caused by well-sharing depends on the size of this wedge and the slope of the marginal revenue curve.

The magnitude of the rotation in marginal cost caused by well-sharing represents the strength of the cost and strategic externalities previously discussed. A key parameter to both externalities is the drawdown faced by one farmer when another extracts water. When multiple farmers draw from the same well, drawdown caused by one farmer's extraction affects everyone sharing the well equally so the effect of the cost and strategic externalities is potentially large. In other words, the magnitude of the clockwise rotation of the marginal cost curve in Figure 1 may be considerable.

2.4.3 Electricity Cost-Sharing

With multiple producers, it can be difficult to calculate individual water use without the appropriate technology. In our sample, about 38 percent of the wells base the cost on the number of hours an individual irrigates (this means that farmers do not share the cost of electricity but rather pay for their own consumption), while 38 percent divide the cost based on land area and another 25 percent split cost in equal shares. The remaining 77 wells are owned by a single producer. The distribution of cost share rules across our sample gives us enough variability to quantify the effect of these cost share rules on irrigation efficiency.

Distributing the cost of electricity based on pre-specified payment rules may introduce further distortions in marginal cost of pumping. To model the distortions of cost share rules, we consider the case of a farmer that pays a pre-specified share s_i of the total electricity bill. The unit cost of water in this case is:

$$P_i^{w,s+ws+cs} = [p^{kwh} - v^{kwh}]\left(a + b\left(w_i + \sum_{j \neq i} w_j\right)\right)\frac{Ws_i}{w_i} \tag{2.7}$$

where $P_i^{w,s+ws+cs}$ denotes unit cost of water under cost share with cs in the superscript indicating cost-sharing, s_i is the share of total electricity bill paid by the i^{th} farmer and the rest is as before. If electricity cost is split based on land area, $s_i = \frac{L_i}{L}$, where L_i is the land endowment of the i^{th} farmer and L is total land area irrigated with water from the well. On the other hand, if the electricity cost is split evenly among farmers, $s_i = \frac{1}{N}$, where N is the total number of farmers drawing water from the same well.

The marginal cost of pumping can then be denoted by:

$$MC_i^{w,s+ws+cs} = [p^{kwh} - v^{kwh}](1+\rho)(a+2bW)s_i \tag{2.8}$$

where $MC_i^{w,s+ws+cs}$ denotes marginal cost of water under subsidy, well share, and cost share and the rest was defined before.

We are interested in identifying conditions under which electricity cost-sharing may reduce the marginal cost of pumping and exacerbate over-extraction. Such a situation occurs whenever $MC_i^{w,s+ws+cs} < MC_i^{w,s+ws}$, which is found to be satisfied if $(1+\rho)s_i < 1$ (derivation of this condition and further discussion can be found in Appendix A). Given the share of the electricity bill assigned to a given farmer, one farmer's pumping increases other farmers' cost even in the absence of drawdown (i.e., even in the absence of cost and strategic externality). This is due to an increase in others' unit cost of water as revealed by Equation (2.7). Equation (2.7) shows that sharing the cost of electricity creates another source of non-excludability resulting from the fact that individual farmers cannot exclude others from their own electricity expenditure. We call this externality "cost share externality".

The effect of the cost share externality with subsidized electricity rates is illustrated in Figure 1 by a clockwise rotation of the marginal cost of pumping from MC_i^{w} to $MC_i^{w,s+ws+cs}$. The specific distortionary effect of cost-sharing is depicted as the wedge between $MC_i^{w,s+ws}$ and $MC_i^{w,s+ws+cs}$. The magnitude of the increase in water pumped caused by cost-sharing will depend upon the size of this wedge and the slope of the marginal revenue curve. In turn, the size of the wedge depends upon the farmer's share of electricity bill and their conjectures about others' reactions to their pumping decisions (parameters s_i and ρ).

Formalization and graphical illustration of the effect of multiple distortions prevalent in Mexico on the marginal cost of pumping allows us to generate testable hypotheses. We now proceed to discuss our hypotheses regarding the drivers of inefficient over-extraction and our strategy for empirical assessment of those hypotheses.

2.5 Hypotheses of this Study

From our discussion of distortions to the marginal cost of pumping, it follows that the number of farmers sharing a well and electricity cost-sharing are both expected to increase groundwater use. But in line with findings in previous studies in other countries and institutional contexts (e.g., Hendricks and Peterson 2012), we expect water demand to be inelastic to its unitary price.

Testing the hypothesis of inelastic water demand requires estimating irrigation demand and its own price elasticity. Due to potential inefficiencies associated with institutional distortions, the dual frontier (e.g., cost or profit functions) is not a neutral transformation of the frontier augmented to incorporate inefficiency and estimates of water demand elasticity from the former may be biased (Kumbhakar 2001). Therefore we estimate a frontier irrigation demand function and allow for inefficiency in the application of irrigation water. We exploit the estimated frontier to measure the effect of the number of farmers sharing a well and the electricity cost share rules on irrigation efficiency.

Radial measures of inefficiency (either input-based or output-based) preclude decomposition of inefficiency scores with respect to a single production input masking differences in efficiency that might be attributed to particular factor inputs (Kopp 1981). This is a limitation worth avoiding, especially when there are reasons to suspect that certain production factors may be used particularly inefficiently. This may be the case with irrigation given the institutional arrangements distorting its marginal cost. Failure to identify inefficiency attributable to a specific input factor hinders input-specific policy design (Sauer and Frohberg 2007). To gauge efficiency in irrigation application, we use an input-specific measure of efficiency developed by Kumbhakar (1989).

2.6 Model

Kumbahkar's model of input-specific efficiency was created for estimation with panel data. Sauer and Frohberg (2007) adapt it to cross-sectional data and divide firms into different groups to measure the input-specific efficiency of each group. In this paper, we follow Sauer and Frohberg (2007) and use cross-sectional data to measure the impact of institutional arrangements (i.e., multiple irrigators pumping from the same well and electricity cost-sharing) on the efficiency with which irrigation is applied. Other physical, hydrological, and socio-demographic variables are also incorporated.

It has been argued (Sauer and Frohberg 2007) that the Symmetric Generalized McFadden (SGM) form is a desirable cost function specification because it is flexible (i.e., it satisfies the second-order flexibility conditions) and at the same time it adheres to theoretical conditions of a cost function as shown by Diewert and Wales (1987). In addition, the SGM specification allows imposition of global concavity conditions and estimation of average input demand functions avoids the "Greene problem"[2] (Sauer and Frohberg 2007). This set of desirable properties make this functional form an appropriate choice for this study.

The SGM cost function is denoted as:

$$C^*(.) = g(p)y + \sum_i b_i p_i + \sum_i b_{ii} p_i y + \sum_i \sum_k d_{ik} p_i q_k y + \sum_k a_k \left(\sum_i \alpha_{ik} p_i\right) q_k + b_{yy}\left(\sum_i \beta_i p_i\right) y^2 + \sum_k \sum_l \delta_{kl} \left(\sum_i \gamma_{ilk} p_i\right) q_k q_l\, y$$

$$i = 1, 2, \dots n, \qquad k, l = 1, 2, \dots m \tag{2.9}$$

where $g(.)$ is a function defined as:

$$g(p) = \frac{p' S p}{2\theta' p} \tag{2.10}$$

where p_i is the price of variable input i; p is the vector of such prices; y is output; q_k and q_l represent quantities of fixed inputs; S is an $n \times n$ symmetric matrix; $\theta = (\theta_1, \dots, \theta_n)'$

[2] When Greene (1980) estimates technical and allocative inefficiency using translog cost function, he finds that the relationship between allocative inefficiency and the total costs of inefficiency is unclear and hard to define in the model. As a result, he assumes that the allocative inefficiency and the total costs of inefficiency are independent to each other, which, as Greene points out, is not a very reasonable assumption. The problem is referred as "Greene problem" by later literature (Bauer 1990; Kumbhakar 1997).

is a vector of nonnegative constants with at least one non-zero element; b_i, b_{ii}, d_{ik}, a_k, α_{ik}, b_{yy}, β_i, δ_{kl}, and γ_{ilk} represent parameters.

Differentiating (2.9) with respect to input price and applying Shephard's lemma, the conditional demand function of input i, x_i^*, is obtained:

$$\frac{dC(.)}{dp_i} = x_i^* = \left(\frac{\sum_j s_{ij}\, p_j}{\sum_r \theta_r\, p_r} - \frac{\theta_i}{2}\left[\frac{\sum_i \ \sum_j s_{ij}\, p_i p_j}{(\sum_r \theta_r\, p_r)^2}\right]\right) y + b_i + b_{ii} y + \sum_k d_{ik} q_k y$$
$$+ \sum_k \alpha_{ik} q_k \ + \beta_i y^2 + \sum_l \ \sum_k \gamma_{ilk} q_k q_l\, y$$
$$i, j, r = 1, 2, \dots, n \qquad k, l = 1, 2, \dots, m. \tag{2.11}$$

Concavity holds for $p_i > 0$ with $i = 1, \dots, n$, $y > 0$ and $q_k > 0$ with $k = 1, \dots, m$, if and only if, the Hessian matrix $S = [s_{ij}]$ is negative semi definite (nsd). Following the procedure outlined in Diewert and Wales (1987) concavity restrictions on S are imposed by re-parameterizing it as $S = -AA'$, where A is a lower triangular matrix of order n, and since p^* is chosen to be a vector of ones, $\sum_i s_{ij} = 0$ for all i. For estimation purpose, b_{yy}, a_k, δ_{kl} are normalized to unity, and θ_i is replaced by the mean values of x_i over the whole sample. This re-parameterization makes $C(.)$ linear homogeneous, monotone and concave in p as well as symmetric (see also Lau 1978, 1986), making the properties of the cost function consistent with economic theory.

Adding systematic inefficiency components and an error term, the conditional demand functions given in (2.11) can be written as follows:

$$x_i = x_i^* + \zeta_{i1} Z_{i1} + \zeta_{i2} Z_{i2} + \cdots + \zeta_{iH} Z_{iH} + v_i \tag{2.12}$$

where each Z_{ih} $(h = 1, \dots, H)$ is a vector of variables $(Z_{ih1}, \dots, Z_{ihG})$ and Z_{ihg} $(g = 1, \dots, G)$ indicates that the observation belongs to group g with respect to characteristic h which may influence the efficiency of input i. For instance, the cost share mechanism is one characteristic in our application. Three groups are observed in our sample with respect to this characteristic: irrigators that split the electricity cost evenly, those that divide the cost based on land area, and those that do not share the cost of electricity. $\zeta_{ih} = (\zeta_{ih1}, \zeta_{ih2}, \dots \zeta_{ihg})$ are vectors of parameters to be estimated. A greater value of

ζ_{ihg} indicates that farmers within group g of characteristic h tend to use more of input i, all else constant.

Inefficiency τ_{igh} of the group g with respect to characteristic h in the use of input i can be calculated through:

$$\tau_{ihg} = \zeta_{ihg} - min_h \zeta_{ihg}. \tag{2.13}$$

An intuitive interpretation of Equation (2.13) suggests that τ_{ihg} represents the reduction in the quantity of input i achievable by switching to the most efficient group with characteristic h holding the application of all other inputs unchanged. The input-specific allocative efficiency of group g with respect to characteristic h in the use of input i is:

$$AE_{ihg} = 1 - \tau_{ihg}/x_{ihg}. \tag{2.14}$$

The percentage cost increase faced by observations belonging to group g within characteristic h due to inefficiency in input i can be calculated by:

$$CAE_{ihg} = p_{ihg}\tau_{ihg}/C_{ihg} \tag{2.15}$$

where C_{ihg} is observed total production cost of farmers in group g with respect to characteristic h.

The measure CAE_{ihg} allows identification of the inputs with the greatest potential for cost savings because it weighs input quantity reductions by their respective prices. As explained by Kumbhakar (1989), one of the advantages of this procedure is that no special distributional assumptions are needed on τ_{ihg}, as independence between τ_{ihg} and other regressors in the demand system is not required.

2.7 Data

A survey of agricultural groundwater irrigators was conducted in Mexico by the Instituto Nacional de Ecología y Cambio Climático (National Institute of Ecology and Climate Change). Data collection on irrigation wells occurred during the 2003-2004 winter. A detailed description of the data collection process can be found in Appendix B.

Cross sectional data was obtained from farmers in a sample of 197 wells. Irrigation wells are uniformly scattered across the country so they are geographically representative of agricultural groundwater irrigators in Mexico. Detailed data on quantity and prices of inputs and outputs were obtained from farmers along with data on irrigation application and cost of electricity used in pumping groundwater. Data includes quantities and prices of three variable inputs (fertilizer, irrigation, and a composite of other inputs including expenditures in land rent and preparation, labor, pesticide, and marketing), and one fixed input (land). A vector of outputs including field crops, fruits, and vegetables were aggregated into one single output applying Jorgenson's procedure for "exact" aggregation (Jorgenson et al. 1987).

Potential sources of inefficiency (i.e., elements of vector Z_{ih} in Equation (2.12)) considered in this study are: mechanism for sharing electricity costs (no cost-sharing, evenly split, or based on area), and the number of farmers in each well (i.e., which can presumably capture pressures from strategic pumping). Control variables include socio-demographic, biophysical, and hydrological variables. Variability in irrigation technology is not observed as the overwhelming majority of farmers (96 percent in our sample) use gravity irrigation systems.

Table 2.2 reports the mean and standard deviation of variables by type of cost share. Some variables have similar distributions in all four groups. For example, the farmer's age and soil type are similar for all four groups. However, we do find systematic differences across groups. Irrigation units that have no cost share (individually-owned wells and the wells that everyone pays for his/her own water use) have a substantially higher average land area (mean of 34.9 and 30.7 hectares) than farmers operating under equal share (7.2 hectares) and share based on land area (8.5 hectares). The education level of farmers with no cost share is higher compared to those with a cost share. These correlations underscore the importance of controlling for education and land area when quantifying the marginal effect of cost share on irrigation efficiency.

Table 2.2: Summary Statistics of Data by Cost share Type

	Shared Wells			Individually Owned Wells
	With Cost Share		No Cost Share	
	Equal for All Users	Based on Land Area		
Consumed water quantity (m^3)	46,743 (36,163)	37,988 (45,363)	95,168 (140,352)	93,685 (169,933)
Pumping cost of water (pesos/m^3)	1.2 (3.3)	1.0 (2.2)	1.7 (4.2)	1.3 (2.5)
Consumed fertilizer quantity (kg)	6,433 (12,121)	6,327 (10,936)	15,838 (18,277)	17,871 (25,292)
Fertilizer price (pesos/kg)	2.4 (1.2)	2.0 (0.7)	3.4 (5.0)	2.5 (1.9)
Land area (hectares)	7.2 (6.0)	8.5 (8.4)	30.7 (38.1)	34.9 (38.3)
Number of farmers sharing one well	13.1 (9.6)	17.5 (16.2)	23.9 (19.1)	1.0 (0.0)
Soil type (1-5)	3.6 (1.1)	3.2 (1.2)	2.9 (0.9)	3.2 (1.0)
Semi-arid or arid climate (climate type dummy =1)	0.7 (0.5)	0.5 (0.5)	0.5 (0.5)	0.6 (0.5)
Well depth (meters)	128.9 (46.4)	129.7 (44.7)	147.3 (57.6)	121.7 (119.8)
Farmers' age (years)	52.9 (9.4)	53.7 (7.8)	51.2 (11.3)	54.6 (11.8)
Education (1-5)	1.6 (0.6)	1.8 (0.9)	2.7 (1.6)	3.0 (1.6)
Share of fruit and vegetable	0.8 (0.4)	0.4 (0.5)	0.3 (0.4)	0.6 (0.5)
Number of observations	30	45	45	77

Mean values are reported and standard deviations are in parentheses.

2.8 Estimation

Following Provencher and Burt (1993), the number of farmers sharing a well is included as an explanatory variable in our estimation. Binary indicators for each electricity cost-sharing mechanism (evenly-based and area-based) are also included. The effect of these variables on irrigation may be confounded with the effect of other drivers such as soil type, climate regime, depth to groundwater, age and education of farmers, and crop types. Obtaining reliable estimates of the link between well sharing, cost share rules and pumping requires controlling for these factors.

The system of equations is specified as:

$$x_i = x_i^* + a_{ni} * N + a_{cs1i} * CS_1 + a_{cs2i} * CS_2 + a_{sii} * SI + a_{cli} * CL$$
$$+ a_{depthi} * DEPTH + a_{agei} * AGE + a_{edui} * EDUCATION + a_{yfvi} * YFV + v_i$$
$$i = water, fertilizer, other\ inputs \tag{2.16}$$

where x_i^* is defined by Equation (2.11) which captures the impact of prices of inputs, outputs, and fixed inputs, N is the number of farmers sharing a well, and CS_1 and CS_2 are the cost share dummies.

Equation system (2.16) also includes controls for soil type ($SI = 1, \dots, 5$, where $SI = 1$ for finest soil and $SI = 5$ for coarsest), depth of well ($DEPTH$) measured in meters to water table, age of the farmer (AGE), education of the farmer (EDUCATION) (i.e., (1) did not finish elementary school, (2) finished elementary school, (3) finished middle-school, (4) finished high-school, (5) more than high-school),[3] climate zone (CL), and crop types (YFV) which is captured by the share of fruit and vegetable in total output as these crops tend to be more water intensive than field crops.

The climate zones are based on the widely used Köppen-Geiger classification system, which are used internationally for consistency between nations and regions. Mellinger, Sachs and Gallup (1999) provide an excellent description of the classification system. Since the climate zones are not ordered based on expected precipitation or irrigation

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[3] Education may be more appropriately captured by a dummy variable for each level of schooling. However, this would create 4 more variables in each equation which would result in a significant increase in the number of parameters to be estimated. Measuring education by a categorical variable increases the parsimony of our model and eases the burden on degrees of freedom with only 197 observations.

requirements, we create two categorical variables for the empirical analysis.[4] The default (omitted) category refers to regions with a temperate climate and a dry winter, while the alternative category refers to regions with a semi-arid or arid climate. We expect that irrigation requirements will be lower in the default category than the alternative category.

With shared wells we do not have sufficient information to attribute input usage and output production to specific farmers so we use the average age and education of surveyed farmers as the socio-demographic variables for the unit. Output includes field crops, fruits, and vegetables. Fruits and vegetables are typically more water intensive than field crops so we include the combined share of fruits and vegetables in total output.

The system (2.16) is estimated using a nonlinear iterative seemingly unrelated regression estimator with Eicker-Huber-White heteroskedastic-consistent standard errors.[5] With three inputs, the matrix S_{ij} is a 3 by 3 matrix, which is recovered from estimation of matrix A.

2.9 Results

Demand equations for water, fertilizer and the composite of other inputs are estimated simultaneously and their R-squared values are 0.74, 0.59, and 0.86 respectively. The coefficients for correlation of error terms across equations are -0.13, 0.10 and -0.02 for water and fertilizer equations, water and the composite input, and fertilizer and the composite input equations respectively.[6] Table 2.3 reports estimation results of the water equation. Results for the other two inputs are reported in Table C.1 in Appendix C. The number of farmers sharing a well does not have a statistically significant impact on

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[4] The limited number of degrees of freedom makes it impossible to estimate coefficients for seven categorical variables based on each unique climate zone.

[5] To impose concavity on the cost function, we have to estimate A_{ij} instead of S_{ij}. While S_{ij} are linear in our model, A_{ij} are not. As a result, a nonlinear SUR regression is used instead of linear regression.

[6] The null hypothesis of no correlation across error terms in the system is strongly rejected at the 1% level of significance with a likelihood ratio of 3690.5 (critical value of 11.34).

Table 2.3: Coefficient Estimates for Water Demand

Water equation	*Estimates*
Constant	-39896.6
	(33315.0)
Output quantity	547.6**
	(247.6)
Interaction of land area and output quantity	-97.5***
	(35.4)
Land area	3208.5***
	(394.9)
Quadratic term of output quantity	2.1**
	(0.9)
Interaction of quadratic land area and output quantity	1.0**
	(0.5)
Dividing electricity bill by share of land area	16456.9**
	(8114.8)
Dividing electricity bill evenly	25801.5***
	(8515.8)
Number of farmers sharing a well	279.0
	(316.5)
Soil type	6566.6
	(5629.1)
Climate type	12315.7
	(14850.1)
Depth of well	42.8
	(54.8)
Age	-227.6
	(419.2)
Education	4078.8
	(4436.3)
Share of fruit and vegetable	3834.3
	(11379.4)
Own price elasticity of water demand	-0.06**
	(0.02)
R^2	0.741
Observations	197

Robust standard errors are in parentheses. Asterisk (*), double asterisk (**) and three asterisk (***) denote that variables are significant at 10%, 5%, and 1% respectively.

irrigation application. This result suggests that strategic pumping caused by well-sharing is weak, at best.[7]

Sharing the cost of electricity evenly has a positive and statistically significant impact on irrigation application. Sharing the cost of electricity based on land area also has a positive but smaller impact. Results of cost share variables are consistent with the hypothesis that cost-sharing reduces irrigation use efficiency.

To ensure that the effect of cost-sharing is not being confounded with the effect of well-sharing, we have also estimated the model with the sub-sample of shared wells only. The effect of electricity cost-sharing is robust to this change, though the reduction in sample size reduces the precision of the coefficients.

Table 2.4: Input-specific Allocative Efficiency and Cost Increase due to Inefficiency

Farmers	Allocative Efficiency	Cost Increase
Farmers paying their own actual electricity consumption	1.00	0%
Farmers dividing electricity bill based on their land share	0.73	5%
Farmers dividing electricity bill evenly	0.58	7%

Parameter estimates are used to calculate efficiency as described by Equations (2.13) and (2.14) and results are reported in Table 2.4. Implementing an evenly split cost share mechanism decreases farmers' irrigation efficiency to 0.58 while implementing a land-based cost share mechanism decreases farmers' irrigation efficiency to 0.73. These results show that a cost share rule which splits the electricity cost evenly among farmers has a stronger effect than a rule establishing cost share based on land area.

Our results show that the cost distortion introduced by electricity cost-sharing is substantial. Cost-sharing creates a situation where a farmer pays only a fraction of the electricity cost of his/her extra pumping. Under an evenly split cost share rule this is

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[7] The model was also estimated with a quadratic term for N and interaction terms between CS_1, CS_2 and N to consider different channels through which well sharing might affect irrigation. We have also estimated a model where N was replaced by a well share dummy. Well sharing had an insignificant effect across all models.

perhaps a small fraction of total electricity cost (e.g., only 20% in a well shared by 5 farmers). Under a land-share rule, larger farmers may not benefit as much as their smaller counterparts. Consequently the effect of an evenly-split cost share rule is found to be larger in magnitude and statistically more robust, than a cost share rule based on land area.

Our results suggest that distortions caused by the cost and strategic externalities (i.e., the magnitude of the clockwise rotation from $MC_i^{w,s}$ to $MC_i^{w,s+ws}$ in Figure 1) are not strong. This may be explained by a small impact of individual pumping on the water level, absence of strategic pumping from farmers sharing the well, or by unobservable self-governance institutions facilitating cooperative behavior. But, if such institutions were effective enough to eliminate the marginal cost-reducing effects of well-sharing, they would also eliminate the effect of electricity cost-sharing mechanisms (rotation from $MC_i^{w,s+ws}$ to $MC_i^{w,s+ws+cs}$ in Figure 1), which does not seem to be the case. Therefore, while the influence of hydrological and institutional features cannot be distinguished in our analysis, results suggest that the insignificant effect of well sharing on pumping is explained by a small impact of an individual's pumping on water level or absence of strategic pumping, rather than the existence of cooperative institutions.

Allocative inefficiency in irrigation application results in production cost that is higher than the minimum cost. The increase in cost for farmers operating under each cost share mechanism can be calculated based on Equation (2.15). The percentage increase in cost due to allocative inefficiency with cost-sharing is reported in Table 2.4. We find that allocative inefficiency associated with area-based (evenly-based) cost share increases total production cost by 5 (7) percent. Therefore in addition to having a significant impact on the overall amount of water pumped, irrigation inefficiency also has a sizable effect on overall production costs. This suggests that removal of inefficiency sources will not only alleviate groundwater depletion but also improve farmers' welfare.

The own price elasticity of demand for irrigation water is reported in Table 2.3 and it is -0.06 (with a bootstrapped standard deviation of 0.02 so the elasticity estimate is significant at 5% level), which means that a doubling of the unitary cost of pumping would reduce irrigation by 6 percent. Thus, only a very substantial increase in pumping cost can have a sizable impact on irrigation.

Some limitations of this analysis are worth noting. The cross sectional nature of our data does not allow us to control for unobservable fixed effects that may be correlated with our explanatory variables. We are able to control for some important time-invariant factors such as soil, climate, and socio-demographic variables, but analysis with cross-sectional data always risks omitted variable bias due to correlation between unobservables and explanatory variables.

This analysis, like the rest of the literature, neglects issues of optimal timing of irrigation. Inefficiencies can emerge not only in terms of the total amount of water applied during the growing season but also in terms of the timing of application. Farmers that share the same well may play a dynamic game in which they deviate from the optimal irrigation schedule if they believe they avoid the drawdown caused by another farmer at the otherwise optimal irrigation time. Finally, a profit maximizing framework may be more appropriate for farmers in this context. However, theoretically consistent and econometrically implementable input specific efficiency measures in the context of a profit dual function are not yet available. Expanding input specific efficiency measurement in this direction seems to be a relevant and promising research avenue.

2.10 Policy Implications

In combination our results show that common pool problems created by the sharing of electricity cost can have a sizable impact on pumping. As summarized by Ostrom in several studies (e.g., Ostrom 1996), conventional solutions to the common pool problem typically include creation of property rights (granting the property of the well to one individual or institution) and government ownership and control. The former can have significant implementation problems and resistance in the field. For the latter to effectively reduce over-extraction regulators would have to: 1) pursue maximization of social welfare as their objective; 2) have knowledge of the workings of ecological and hydrological systems; and 3) have knowledge of institutional changes that would induce socially optimal behavior.

An alternative solution that has spontaneously emerged in the field and later formalized by Ostrom et al. (1999) is that of self-governance. Our results seem to indicate that self-governance institutions inducing cooperative behavior may not have been in place in Mexico during the time of the survey or that they were not sufficient to prevent considerable inefficiency from the common pool problem created by electricity cost-sharing rules. Self-governance cannot be successfully implemented everywhere. Conditions like feasible improvement of the resource, trust among users, and users' discount rate influence the chances of successful self-governance of a natural resource. Therefore the success of these institutional reforms will be determined by the idiosyncrasies of wells and regions in Mexico. An ex-ante evaluation of alternative institutional arrangements to solve the common pool problem of groundwater in Mexico constitutes an undoubtedly important research avenue in the future.

A much simpler, yet promising solution to the cost share problem is facilitating implementation of metering systems and allocation rules that allow charging each farmer for his own consumption. This is especially true for those wells that divide electricity costs evenly among farmers. In some cases, there may be financial barriers to adoption of these technologies and, in others, social ones. Public policies should be aimed at removing the barriers preventing adoption of more modern metering systems.

The magnitude of the own price elasticity of demand suggests that elimination of the electricity subsidy by itself is not an effective policy for a significant reduction of groundwater pumping. This result, along with the impact of cost share variables on irrigation demand, suggest that elimination of cost share mechanisms seems a much more promising conservation policy than price-based instruments. In addition, intuition suggests that the latter will have a negative effect on farmers' welfare while the former, by eliminating cost inefficiencies shown in Table 2.4, may result in higher welfare for farmers.

2.11 Conclusions

The objective of this study was to quantify the role of different sources of non-excludability on irrigation water demand in Mexico. We model three potential distortions of the marginal pumping cost of groundwater, and empirically gauge their impacts on irrigation demand. Based on insights from the theoretical model of marginal cost of pumping, we hypothesize that electricity subsidies, well sharing and electricity cost-sharing will increase groundwater pumping and aggravate groundwater depletion.

Our results are consistent with the hypothesis that electricity cost-sharing decreases farmers' irrigation efficiency. In fact, results suggest that cost-sharing is at the heart of water over-extraction observed in many areas in Mexico. Both cost share rules have a statistically and quantitatively significant effect on pumping. Moreover, our results are consistent with the hypothesis that water demand is inelastic and, thus, eliminating the electricity subsidy is unlikely to result in a substantial reduction in irrigation. We estimate that the price elasticity of irrigation is only -0.06, which means that a doubling of the unitary cost of pumping would only reduce irrigation by 6 percent. In contrast, the hypothesis that well sharing will decrease irrigation efficiency is rejected. Our results indicate that the number of farmers sharing a well does not have a statistically significant effect on individual pumping, which suggests either a limited effect of individual pumping on water level or absence of strategic pumping by farmers sharing the wells.

Concerning the effect of these policies on farmers' welfare, one needs to consider that policy instruments reducing inefficiency need not cause a reduction in farmers' surplus. This is because increases in individual marginal cost due to institutional reforms may be offset by 1) reductions in pumping cost associated with a decrease in the total volume pumped, and 2) an increase in water's marginal value product due to enhanced production efficiency. In other words the alleviation of externalities increases overall welfare and this tends to offset the raise in individual pumping costs introduced by policy. We suggest that policymakers consider all of these effects when making decisions about changes to existing electricity and water policies.

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CHAPTER 3 DYNAMIC ADJUSTMENT IN AGRICULTURAL PRACTICES TO ECONOMIC INCENTIVES AIMING TO DECREASE FERTILIZER APPLICATION

3.1 Introduction

It is widely acknowledged that fertilizer (e.g., nitrogen and phosphorus) use in agricultural production and the associated runoff leads to high levels of water pollution in the surrounding watershed area, as well as downstream (Goolsby et al. 2001; Rabotyagov et al. 2010; Yuan et al. 2013; Rebolledo et al. 2016). The application rate of fertilizer on a certain area of land is one of the key factors influencing water pollution: all else equal, a higher fertilizer application rate leads to a larger amount of nutrient migrating from the soil into the water system (Angle et al. 1993; Jaynes et al. 2001). When fertilizer is overused the surplus of nutrition in the soil is more likely to cause water pollution (Angle et al. 1993; Andraski et al. 2000). Past research finds that farmers often overuse fertilizer to avoid potential loss in yield associated with uncertainty in weather and soil nutrition levels (Sheriff 2005; Stuart et al. 2014). As a result, a major policy focus is on minimizing the impact of fertilizer application on environmental systems. We contribute to this policy discussion by shedding light on the dynamics and relative cost-effectiveness of input- and output-based policies that use financial incentives to influence farmer behavior.

Input- and output-based policies refer to policies that target the prices of inputs or outputs in production; for example, a policy that affects the prices of fertilizer used in production is an input-based policy and a policy that affects the price of crops grown on a parcel of land is an output-based policy. This definition is different from another definition in which an input refers to a variable in the polluter’s choice set of variables that influence pollution runoff. In this latter case, an input-based policy is one that targets these choice variables, instead of directly targeting emissions or their proxies (see Shortle and Horan 2013 for further discussion).

Different crops have different requirements for fertilizer application. Corn is a particularly fertilizer-intensive crop. According to data published by the Economic Research Service at the United States Department of Agriculture (USDA ERS), the average application rate of nitrogen for corn production in the United States in 2002 was 154 kg/hectare. The average rate of phosphate application was 67 kg/hectare. Conversely, soybeans is a fertilizer-saving crop with an average application rate of nitrogen and phosphate being only 24 and 55 kg/hectare. Not surprisingly the production of corn usually leads to higher levels of water pollution than soybeans. Research finds that continuous corn cultivation causes a higher level of nitrogen runoff than a corn-soybean rotation (Weed and Kanwar 1996; Kanwar et al. 1997) because of its repeated high rate of fertilizer application year after year (Andraski et al. 2000). For these reasons, crop choice is another important factor influencing water pollution, and consequently, another channel through which policy can exact reductions.

Though a variety of policy options are available for targeting improvements in water quality via a reduction in fertilizer runoff, economists have long favored financial incentives. Financial incentives induce a change in farmer behavior in a manner consistent with environmental conservation without dictating the means of conservation. This allows each farmer to select his/her best option for reducing runoff, which renders financial incentives more efficient than command-and-control policies (Hahn 2000; Whittaker et al. 2003). In the context of fertilizer application, financial incentives may increase the cost of fertilizer (input-based policies) or reduce the profitability of a fertilizer intensive crop, such as corn (output-based policies).

Input-based policies may operate as a tax on fertilizer use or a subsidy on fertilizer reduction, and have been implemented internationally. In the United States, Wisconsin, Iowa and Nebraska have levied taxes on fertilizer application (Larson et al. 1996; US EPA 2001). In Europe, Austria, Denmark, Finland, Italy, Norway and Sweden have also implemented a fertilizer tax to reduce fertilizer application (Rougoor et al. 2001; Söderholm and Christiernsson 2008; Vojtech 2010).

Output-based policies encourage farmers to substitute to less fertilizer-intensive crops by either taxing fertilizer-intensive crops or subsidizing fertilizer-saving crops. Florida has levied a tax on fertilizer-intensive crop acreage to reduce phosphorus loadings from cropland (Ribaudo 2001). Another policy that has been suggested is to couple an environmental standard with federal commodity program payments to reduce fertilizer use (USDA ERS 2007, 2011). Such a policy might affect the profitability of different crops, and lead to the reduction in fertilizer use. In the Corn Belt, corn and soybeans are the main crops that receive government payments. For example, in Iowa, corn and soybeans account for 69 and 30 percent respectively in the total base acres of covered commodities by the payment programs (Plastina et al. 2016). Given the differences in the production practices of corn and soybeans, imposing an environmental standard as a condition for commodity program payments would increase the compliance costs of corn production relative to soybean production, which in turn would decrease the relative profitability of corn.

Several studies evaluate the relative efficiency of both input- and output-based policies. The findings from these studies are mixed. In terms of a reduction in net farm income, Huang and Lantin (1993) find that the cost per pound of reducing excess nitrogen fertilizer application is lower for input-based policies relative to output-based policies. Wu and Tanaka (2005) find that a fertilizer-use tax is more cost-effective than incentive payments. Using a general equilibrium model of the United States economy, Taheripour et al. (2008) find that output-based policies are more efficient for achieving goals with lower nitrogen reduction, but input-based policies become more efficient when higher levels of nitrogen reduction are targeted. In contrast, Bourgeois et al. (2014) find that mixed policies that combine both input- and output-based policies are more cost-effective than any single policy.

The literature that evaluates the relative merits of economic policies targeting water quality and fertilizer runoff typically do so on the grounds of relative cost-effectiveness (Hahn 2000; Shortle and Horan 2001, 2013). Comparing policies from a Pareto-efficiency point of view that considers all social costs and benefits of the policy is often impractical because of the informational requirements associated with the Pareto criterion.

The cost-effectiveness criterion does not attempt to identify policies capable of attaining the optimal level of pollution that maximizes social welfare as does the Pareto-efficiency criterion. Instead, it identifies the policy instrument that attains an exogenously given environmental target (optimal or not) at minimum cost. The cost-effectiveness criterion has been applied to evaluate command-and-control policies as well as financial incentives. The former include policies encouraging best management practices or land retirement (Khanna et al. 2003; Wu and Tanaka 2005; Rabotyagov et al. 2010). The latter include tax/subsidy policies based on agricultural input usage or ambient pollution concentration levels (Kampas and White 2002; Wu and Tanaka 2005; Bourgeois et al. 2014). Following this literature, we use the cost-effectiveness criterion.

One limitation in the scope of existing research that we address in this paper is that previous research focuses on the overall long-term effectiveness of the policy – i.e., how much water pollution reduction is achieved once the effect of the policy is fully realized. Past research provides valuable insight; yet, an important, practical aspect of this policy discussion is the speed at which each type of policy takes effect, or how long each policy takes to achieve these (previously estimated) goals. Understanding the dynamics of full adjustment is a crucial factor in assessing the relative cost-effectiveness of input- and output-based policies. If a particular type of policy is known to be more effective, yet takes a substantially longer time to yield these effects, then that policy may in fact be less desirable from an environmental vantage.

Decreasing the application rate of fertilizer on a certain area of land or switching land allocation from a fertilizer-intensive crop to a fertilizer-saving crop are both able to reduce fertilizer use. While the adjustment of the application rate of fertilizer can be rapid, the adjustment of land allocation across different crops may be sluggish and require a long time to be fully realized. Because of crop rotational effects and quasi-fixed capital constraints (Orazem and Miranowski 1994; Arnberg and Hansen 2012), farmers respond slowly to policies targeting adjustments in land allocation. Vasavada and Chambers (1986) find that it takes two years for total agricultural land to adjust to its optimal level when land is treated as one single input. When land is divided across different crops, Lansink and Stefanou (1997) find that it takes more than twelve years to adjust land allocation between root crops and other crops. This sluggishness in the adjustment of land allocation affects the speed at which economic policies affect fertilizer application.

To simultaneously assess both the magnitude of input- and output-based policy effects and the speed at which the policies take effect, we deploy an empirical dynamic adjustment model of corn production that takes fertilizer as one of several inputs into production. We estimate the dynamic response of fertilizer use to changes in the price of both fertilizer (input-based policy) and corn (output-based policy). By estimating the response of fertilizer use to changes in the prices of fertilizer and corn, we are able to measure the effect of each type of policy on fertilizer use. By estimating the adjustment rate of the quasi-fixed inputs (capital and land allocated to corn), we can measure the total time required for the policy to take full effect.

We use county-level data because it is more policy-relevant than farmer level data, as policymakers are interested in affecting change over a relatively large area. This focus is advantageous when we consider the possibility that, while individual farmers may respond to policy-induced incentives slowly, the aggregate response in a county may be less sluggish if the total adjustment can be achieved through adjustments made by the farmers with relatively low adjustment costs and higher adjustment rates.

3.2 Theoretical Foundation and Empirical Specification

3.2.1 Theoretical Foundation

We start by following previous literature (e.g., Hennessy 2006; Du and Hennessy 2012) and assume that farmers make production decisions (including the amount of fertilizer applied) to maximize profits. To the extent that fertilizer application may also affect skewness and kurtosis of the yield distribution (Du et al. 2012), farmers' degree of risk aversion and perception of fertilizer impacts may also influence their use. Unfortunately, no information is available that allows construction of a reliable measure of risk aversion. Nor is there information available to quantify farmers' perception of the effects of fertilizer on the probability distribution of yields. Therefore with the caveat that there may be other motivations shaping the decision on fertilizer application, we move forward with our conventional assumption of profit maximization.

Our model is a version of the dynamic duality model that has been widely used to study the adjustment of quasi-fixed inputs in an agricultural context (e.g., Vasavada and Chambers 1986; Luh and Stefanou 1991; Lansink and Stefanou 1997, 2001). The foundation of the model is the maximization of the discounted flow of profit for a producer of multiple outputs using variable inputs and quasi-fixed inputs (Epstein 1981; Epstein and Denny 1983; Lansink and Stefanou 1997):

$$J(v,w,K,Z,t) = \max_{I} \int_{t}^{\infty} e^{-rs}\left[\pi(v,K(s),Z(s),s) - w'K - C\big(I(s)\big)\right]ds. \tag{3.1}$$

In Equation (3.1), $J(\cdot)$ is the value function; K is a vector of quasi-fixed inputs; π is defined as vQ; Q is a vector of netput (output and variable input) quantities that is positive for outputs and negative for inputs; v and w are vectors of market prices of netputs and quasi-fixed inputs, respectively; Z is a vector of fixed inputs; r is the discount rate; s and t reflect technological progress as a time trend; I is the corresponding quasi-fixed input adjustment; and $C(I)$ is the adjustment cost function.

The Hamilton-Jacobi equation of the optimization problem in Equation (3.1) is

$$rJ(v,w,K,Z,t) = \max_{I}\{\pi(v,K,Z,t) - w'K - C(I) + (I - \delta K)'J_k\} + J_t, \tag{3.2}$$

where δ is the depreciation rate of quasi-fixed inputs, and the subscript notation defines a partial derivative (e.g., $J_t = \partial J(\cdot)/\partial t$). Differentiating (3.2) with respect to v, results in the following netput equations:

$$Q = rJ_v - J_{kv}\dot{K} - J_{tv}, \tag{3.3}$$

where $\dot{K}$ ($\dot{K} = I - \delta K$) is the adjustment of K. Differentiating (3.2) with respect to w, results in the following adjustment equations:

$$\dot{K} = J_{kw}^{-1}(rJ_w + K - J_{tw}). \tag{3.4}$$

A common assumption is that producers make optimal decisions based on information in the current period and their expectations of prices, which are assumed to be static (Epstein 1981; Epstein and Denny 1983; Lansink and Stefanou, 1997). This assumption excludes uncertainty in future prices faced by farmers. Alternative assumptions, such as quasi-rational expectations, typically require a relatively long time series of price data to generate expected prices. Given other data requirements (see Section 3.3), the temporal dimension of our data is restricted to the years 2001 to 2008, which is not long enough to facilitate estimation under alternative assumptions.

3.2.2 Empirical Specification

We use a normalized quadratic specification to parameterize the optimal value function. To operationalize the normalized quadratic setup, we use soybeans as the numeraire which allows us to focus on the production of corn. Even though the results in the normalized quadratic design are not invariant to the choice of the numeraire, it is widely used because it is flexible, yet empirically straightforward to implement (Lansink and Stefanou 2001). These are important properties in our case, as limited degrees of freedom render estimation of a complex model and imposition of constraints difficult.

Specifically, the normalized quadratic value function is given by

$$\begin{aligned} J(v,w,z,K,t) = (a_1 a_2)\begin{pmatrix} v \\ w \end{pmatrix} + \frac{1}{2}(vw)\begin{bmatrix} A & C \\ C' & B \end{bmatrix}\begin{pmatrix} v \\ w \end{pmatrix} \\ + \frac{1}{2}(z'K't')\begin{bmatrix} D & G & H \\ G' & E & L \\ H' & L' & F \end{bmatrix}\begin{bmatrix} z \\ K \\ t \end{bmatrix} \\ + (v'w')\begin{bmatrix} O & P & R \\ S & M^{-1} & U \end{bmatrix}\begin{bmatrix} z \\ K \\ t \end{bmatrix}. \end{aligned} \tag{3.5}$$

In Equation (3.5), v, the vector of netput prices includes the price of corn, fertilizer, and labor; w, the vector of quasi-fixed input prices, includes the rental price of corn land and the shadow price of capital; z, the fixed input, is total cropland; the vector of quasi-fixed inputs, K, includes corn land and capital; and t is a time trend. All prices are relative to the price of soybeans, and all other notation defines matrices of parameters to be estimated.

Following Equation (3.3), the netput equation (in our empirical model, the supply of corn, and the demand for fertilizer and labor) is

$$Q^* = r(a_1 + A'v + C'w + O'z + P'K + R't) - P'\dot{K} - R, \tag{3.6}$$

and following Equation (3.4), the adjustment equation for quasi-fixed inputs (corn land and capital) is

$$\dot{K} = (r + M)K + rM(a_2 + B'w + C'v + Sz + Ut) - MU. \tag{3.7}$$

Equation (3.7) defines a linear relationship between multiple factors and quasi-fixed input adjustment, and is sometimes referred to as a multivariate linear accelerator

$$\dot{K}^* = (r + M)(K - K^*) \tag{3.8}$$

where K^* is the optimal level of quasi-fixed input K written as

$$K^* = rN(a_2 + B'w + C'v + Sz + Ut) - NU, \tag{3.9}$$

$$N = -(r + M)^{-1}M. \tag{3.10}$$

In Equation (3.8), $(r + M)$ is the adjustment rate matrix of quasi-fixed inputs K to their optimal level K^*. This multivariate accelerator allows the adjustment of one quasi-fixed input to influence the adjustment of the other quasi-fixed input. In our empirical model, we allow adjustments in corn land and capital to affect each other; we then test for significance of these mutual effects.

3.2.3 Measuring Short-Term and Long-Term Effects

This model allows us to measure both the short-term and long-term response of input use to a change in price; hence, we can assess the short-term and long-term effect of a policy that influences the price of corn or fertilizer on fertilizer application. The difference between the short-term and long-term effects comes from sluggish adjustments in the quasi-fixed inputs. In the short-term, the quasi-fixed inputs are assumed to be fixed at their current level, while in the long-term they are assumed to adjust to their new optimal levels given a new set of equilibrium conditions created by the policy. To make these assessments, we use our model to compute short-term and long-term elasticities – short-term elasticities keep the quasi-fixed inputs constant, and long-term elasticities allow for complete adjustment of quasi-fixed inputs to their long-term optimal level.

Following standard definitions of short-term and long-term elasticities (Morrison and Berndt 1981; Luh and Stefanou 1993; Richards 1999), the short-term price elasticity of each netput to a netput price change is

$$\varepsilon^{s}_{Q_i V_j} = \left(\frac{\partial Q_i}{\partial V_j}\bigg|_{k_1=\bar{k}_1, k_2=\bar{k}_2}\right)\left(\frac{V_j}{Q_i}\right) \tag{3.11}$$

where i and j index the netputs and netput prices. Hence, the short-term elasticity given in Equation (3.11) allows us to assess the sensitivity of the quantities of corn, fertilizer and labor to prices, including both own and cross-price effects.

The short-term price elasticities of netputs to changes in quasi-fixed input prices is

$$\varepsilon^{s}_{Q_i W_j} = \left(\frac{\partial Q_i}{\partial W_j}\bigg|_{k_1=\bar{k}_1, k_2=\bar{k}_2}\right)\left(\frac{W_j}{Q_i}\right) \tag{3.12}$$

which allows us to understand how the netput quantities respond to changes in the price of corn land and capital.

Since, in the short term, quasi-fixed inputs are held constant and do not adjust, changes in the price of corn or fertilizer only affect fertilizer application under the current land allocation and capital level. That is, these short-term elasticities do not account for indirect effects of price changes through adjustments in capital or land allocation.

The long-term price elasticity of netputs to a change in the netput price is

$$\varepsilon^{l}_{Q_i V_j} = \left(\frac{\partial Q_i}{\partial V_j}\bigg|_{k_1=\bar{k}_1, k_2=\bar{k}_2}\right)\left(\frac{V_j}{Q_i}\right) + \left(\sum_{m=1}^{2}\frac{\partial Q_i}{\partial {K_m}^*}\frac{\partial {K_m}^*}{\partial V_j}\right)\left(\frac{V_j}{Q_i}\right) \tag{3.13}$$

and the long-term price elasticity of netputs to a change in quasi-fixed input prices is

$$\varepsilon^{l}_{Q_i W_j} = \left(\frac{\partial Q_i}{\partial V_j}\bigg|_{k_1=\bar{k}_1, k_2=\bar{k}_2}\right)\left(\frac{V_j}{Q_i}\right) + \left(\sum_{m=1}^{2}\frac{\partial Q_i}{\partial {K_m}^*}\frac{\partial {K_m}^*}{\partial V_j}\right)\left(\frac{V_j}{Q_i}\right). \tag{3.14}$$

Notice that Equations (3.13) and (3.14) have additional terms that do not appear in Equations (3.11) and (3.12). These terms – the summations over m – refer to the indirect effects that the changes in input and quasi-fixed input price have on the netput quantities via adjustment in the quasi-fixed inputs. That is, the long-term elasticity is calculated by adding to the short-term elasticities (the first terms in Equations (3.13) and (3.14)) the effects associated with adjustment in the quasi-fixed factors. This is an important part of the total effect since a change in the price of corn or fertilizer induced via policy not only causes a change in fertilizer application directly, but also causes a change in both land allocated to corn and capital which in turn causes a change in fertilizer application.

The long-term price elasticity of quasi-fixed inputs with respect to netput price, captured in the second term of Equation (3.13), is

$$\varepsilon^{l}_{K_m V_j} = \left(\frac{\partial K_m{}^{*}}{\partial V_j}\right)\left(\frac{V_j}{K_m}\right) \tag{3.15}$$

and the long term price elasticity of quasi-fixed inputs to a change in quasi-fixed input prices is

$$\varepsilon^{l}_{K_m W_j} = \left(\frac{\partial K_m{}^{*}}{\partial W_j}\right)\left(\frac{W_j}{K_m}\right). \tag{3.16}$$

These elasticities allow us to measure how a change in the prices of corn land and capital affect the quantity of each of these quasi-fixed inputs.

3.3 Description of the Data

Our analysis focuses on the Wabash River Watershed, which covers 65 counties in Indiana, 23 counties in Illinois, and a small part of Ohio. In this watershed, corn and soybeans are the main crops produced. In 2014, the planting area of corn and soybeans in Indiana constitutes 47.5 and 44.3 percent of the total planting area of field crops; in Illinois, these percentages are 51.7 and 42.6 percent for corn and soybeans, respectively (USDA NASS). We focus on the county level of aggregation to understand how incentives to change agricultural management practices influence water quality over a larger geographic area. Because certain data are missing for some counties, our analysis covers 44 counties in Indiana and 16 counties in Illinois, for a total of 60 counties. Figure 3.1 provides a map of the Wabash River Watershed and the counties included in our analysis. The counties in our analysis are distributed somewhat uniformly across space; hence, we maintain representative coverage over the watershed area despite missing data.

Our dataset is an unbalanced panel that spans the years 2001 to 2008, providing a total of 384 county-year observations. We exclude the 2009 to 2012 years because a preliminary analysis indicated that the data spanning these years is too heavily impacted by the Great Recession. The empirical model requires quantity and price data for all outputs, variable inputs, and quasi-fixed inputs, as well as quantity data for fixed inputs.

We focus on two outputs, corn and soybeans since the production of corn and soybeans constitutes more than 90 percent of all crop production in the Wabash River Watershed area; further, corn and soybeans are typical fertilizer-intensive and fertilizer-saving crops, respectively. We include two variable inputs, fertilizer and labor; two quasi-fixed inputs, capital and land allocated to corn; and one fixed input, total cropland. Since we only focus on corn and soybean production, total cropland is the sum of land allocated to corn and land allocated to soybeans.

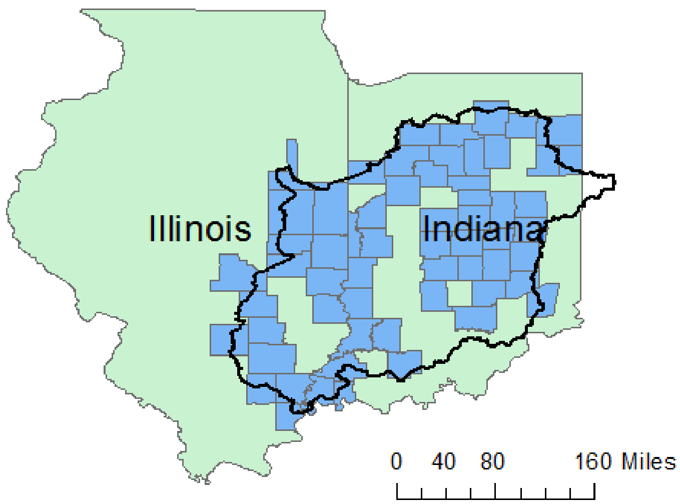

Figure 3.1: The Wabash River Watershed

The bold (black) line in this figure shows the geographical position of the Wabash River Watershed as it spans most of Indiana and part of Illinois. The counties included in our analysis are indicated and shaded in blue.

Data on the production quantity of corn and soybeans, the land area allocated to corn and soybeans, the price of land, the price and quantity of capital, and the price of fertilizer are obtained from the United States Department of Agricultural National Agricultural Statistics Service (USDA NASS). Both the quantity and price of labor come from the United States Bureau of Labor Statistics. We use county level data on the number of employees in the crop production industry and their wages. The land price data are census data, and only have one observation every five years. We use a cubic polynomial interpolation to construct annual land price data; we explored, county by county, several different interpolation techniques (both linear and nonlinear), and we found that the cubic polynomial provided the best fit to most of the counties in our analysis. To further increase the reliability of the interpolation, we use 5-year census data from 1982 to 2012, so that the interpolation is based on a longer time span. Further, we calculate the rental price of land as 4 percent of its value, which is consistent with the proportion of cash rent of farmland in its value in Indiana reported by Dobbins and Cook (2001-2008) at the time span of our data.

Machinery and equipment data are used to measure capital. The price of capital is a price index of machinery and equipment. To measure the machinery cost paid by farmers each year, we construct the shadow price of machinery via $SP = OP(r + \delta)$ (Morrison and Berndt 1981), where SP indicates the shadow price, which is equal to the original price, OP, multiplied by the sum of the discount and depreciation rates, r and δ, respectively. We assume $(r + \delta)$ is 0.15. The quantity of machinery is recovered by dividing the market value of machinery and equipment by the price index. As a result, not only the quantity, but also the quality of machinery, is reflected in the quantity of machinery variable. Since the market value of machinery comes from the 5-year census, we use the same polynomial interpolation based on data from 1982 to 2012 to construct the annual data series.

County level fertilizer quantity data come from the Offices of the State Chemist in both Indiana and Illinois. These offices record all reported sales of fertilizer by fertilizer companies and sales agents in each county. An ideal measurement of fertilizer quantity is the quantity of fertilizer applied to the field in each county; however, this data is largely unobservable. In the absence of observable fertilizer application data, the quantity sold is a reasonable measure. Given transportation and storage costs, most farmers do not purchase fertilizer from outside the county, or store purchased fertilizer for future use. Therefore, the fertilizer sales data is a reliable proxy for fertilizer used in each county. Since fertilizer application occurs after the sale, and the fall application of fertilizer is usually for production in the following year, we measure fertilizer application each year as the sum of fall sales from the previous year and spring sales from the current year. The fertilizer price data is the weighted average price of different types of fertilizers (specifically, 09-23-30, 10-10-10, 10-20-20,10-34-00, 11-52-00, 13-13-13, 16-20-00, 17-17-17, 18-46-00, 19-19-19, Anhydrous Ammonia, Muriate of Potash 60% K20, Nitrogen solution 32%, Superphosphate 44-46%, and Urea 45%). Our calculation of the fertilizer price index follows the same criterion used by USDA NASS.

The price of corn and soybeans is the cash price data for each crop, obtained from GeoGrain. The GeoGrain data is available at the grain elevator level, measured on monthly intervals. To construct county-level data, we obtain averaged cash prices across all elevators in each county; the data are averaged temporally to obtain annual prices. Since crop prices are unknown when farmers make production decisions during the planting season, we use crop prices from the previous year to measure the expected price in the current year.

Theoretically the adjustment of quasi-fixed inputs is a continuous measurement. In empirical research it is common to deploy a discrete approximation: $\dot{K}_t = K_t - K_{t-1}$ (see, for example, Epstein and Denny 1983; Hsu and Chang 1990; Luh and Stefanou 1991, 1993; Fernandez-Cornejo et al. 1992; Boetel et al. 2007).

Table 3.1 provides a statistical description of the data. The table reveals that about 72,000 hectares were planted in corn and soybeans on average, but that there is substantial variation in total area planted that ranges from 4,600 to 220,000 hectares. On average, about half of the total planted area is allocated to corn and the other half to soybeans. Corn price is, on average, 40 percent of the soybean price per metric ton, while corn production measured in metric tons is 3.2 times higher than soybean production. More importantly about 31,000 metric tons of fertilizer is applied, on average. Preliminary statistical analysis indicates a high correlation between corn production and fertilizer application.

Table 3.1: Descriptive Statistics

	Mean	Standard Deviation	Maximum	Minimum
Corn production in a county (metric tons)	354,075.5	214,078.4	1,509,022.6	9,497.4
Soybean production in a county (metric tons)	109,590.4	55,750.4	368,297.8	5,045.8
Corn price ($/metric ton)	92.0	21.0	145.9	67.4
Soybean price ($/metric ton)	222.7	44.6	309.2	160.7
Fertilizer quantity applied in a county (metric tons)	30,764.7	19,308.0	185,635.1	1,232.0
Fertilizer price ($/metric ton)	391.9	161.2	740.4	228.0
Hired labor (persons)	78.7	78.4	472.0	5.0
Wage ($/week)	481.8	146.6	977.0	113.0
Planting area of corn (hectares)	36,625.8	19,161.2	129,099.3	1,821.2
Planting area of soybean (hectares)	35,107.3	16,215.5	106,840.8	2,306.8
Land price ($/hectare)	7,694.5	1,830.7	16,143.1	3,628.0
Total planting area of corn and soybean (hectares)	71,733.1	34,480.7	220,156.8	4,613.6
Composite machinery quantity	442,184.7	176,923.3	1,325,330.6	49,602.2
Composite machinery price	171.6	21.5	209.0	144.0

The total number of counties included in our analysis is 60.

3.4 Results

We estimate the parameters in the system defined by Equations (3.6) and (3.7) via a fixed effect seemingly unrelated regression (SUR) procedure. In total, after imposing the theoretically relevant cross-equation restrictions, there are 35 parameters. Given these parameter estimates, we can compute the short-term and long-term price elasticities and conduct our policy analysis. We report the parameter estimates and standard errors in Table E.1 in the appendix for reference. Our profit function specification provides significant flexibility (i.e., is able to capture a wide range of behavioral responses). The downside is that this specification results in estimation of a large number of parameters which, in combination with cross-equation restrictions, results in violation of the theoretical property of convexity of the profit function in a number of data points. This is relatively common in estimation of dual profit or cost functions (e.g., Lansink and Stefanou 1997).

3.4.1 Short-Term Adjustments

Table 3.2 reports the short-term price elasticities for output (corn) and the variable inputs (fertilizer and labor), with respect to prices of the netputs and quasi-fixed inputs. The table is organized so that the rows represent each of the netput quantities, and the columns represent the netput and quasi-fixed input prices from which each of the elasticities are computed.

Most partial effects are of the expected sign. Given our objective, we focus on the intensive and extensive margin changes for fertilizer application. The own price elasticity of corn is 0.30, indicating that a 1 percent increase in the price of corn relative to soybean induces a 0.30 percent increase in corn supply. The own price elasticity of fertilizer is -0.96, which indicates that when the fertilizer price increases by 1 percent, the application of fertilizer decreases by 0.96 percent. This elasticity is statistically significant, and indicates that any policy that increases the price of fertilizer, such as taxing fertilizer use or subsidizing a reduction in fertilizer application, is an effective means of reducing fertilizer application in the short-term.

Table 3.2: Estimates of the Short-Term Price Elasticity

		Price				
		Corn	Fertilizer	Labor	Land	Machinery
Quantity	Corn	0.30***	-0.34***	-0.01	-0.14***	0.00
		(0.09)	(0.09)	(0.01)	(0.02)	(0.06)
	Fertilizer	0.96***	-0.96***	-0.01	-0.40***	0.55***
		(0.24)	(0.28)	(0.04)	(0.07)	(0.19)
	Labor	0.12	-0.07	-0.33***	-0.11	0.47**
		(0.21)	(0.23)	(0.08)	(0.10)	(0.20)

All estimated elasticities are constructed using parameter estimates shown in Table D.1 from the fixed effects seemingly unrelated regression. Standard errors are calculated using the delta method, and ***, **, * indicates significance at 1, 5, and 10 percent levels.

The elasticity value reported here reveals a negative link between fertilizer usage and its own price. Behind this negative effect is the physical relationship between nitrogen and corn yields. Evidence from the agronomic literature suggests that increased nitrogen application raises corn yields at a decreasing rate. Therefore producers would respond to changes in the price of fertilizer. Our elasticity is larger (in absolute value) than the elasticity that can be inferred from agronomic studies. In fact, in the study area, the elasticity suggested by agronomic studies based on field data is around -0.3 (Iowa State University, 2016). Differences are perhaps due to the level of aggregation. The economically optimal nitrogen rate (EONR) suggested by Iowa State extension services are based on field level information. The spatial unit of observation in this study is a county. Effects over an entire county incorporate a large heterogeneity in response. Typical agronomic units (as the ones considered to calculate the EONR) are included, but marginal units which tend to be more sensitive to changes in price are also included in our study.

We also find that the short-term cross-price elasticities between corn and fertilizer are statistically significant. The short-term cross-price elasticity between the quantity of fertilizer and the price of corn is also close to 1; specifically, a 1 percent decrease in the relative price of corn leads to a 0.96 percent decrease in the application rate of fertilizer. This result indicates that policies that discourage planting corn by reducing its relative price can also lead to a significant reduction in fertilizer application through adjustment in the application rate. The downside of reducing fertilizer application via land use adjustment is a reduction in corn production. In fact, a 1 percent increase in the price of fertilizer leads to a 0.34 percent reduction in the quantity of corn produced.

In percentage terms the response in fertilizer application to either a decrease in the price of corn or an increase in the price of fertilizer is (statistically) the same. These results imply that policies directed towards decreasing the price of corn and policies directed towards increasing the price of fertilizer are equally effective in reducing fertilizer application, at least in the short-term. Estimated elasticities are consistent with prior expectations based on economic theory and agronomic relationships, lending credence to our empirical framework. Additionally, elasticity estimates imply that policies that increase the price of land or decrease the price of machinery can also influence fertilizer application.

3.4.2 Long-Term Adjustments

In the long-term, both corn land area and machinery adjust to their optimal levels; these adjustments lead to further change in fertilizer application. The long-term elasticity estimates are reported in Table 3.3, and are not generally different from the short-term elasticity estimates in Table 3.2. From the short-term to the long-term the magnitude of the own-price elasticity of fertilizer increases only from -0.96 to -0.98, which means that most of the adjustment occurs within the short-term (i.e., one year) and at the intensive margin. In particular the additional effects from the adjustment in the two quasi-fixed inputs (i.e., the second terms in Equations (3.13) and (3.14)) are not substantial. This can be explained by a small elasticity of fertilizer with respect to corn acreage and machinery, a small elasticity of corn acreage with respect to netput prices and machinery prices, or by a mutual offsetting effect between these impacts. We explore these details in a subsequent section.

Looking at elasticity estimates over different time horizons, it is clear that input-based policies that affect the relative price of fertilizer are effective both in the short-term and long-term. Our results are consistent with the findings from several studies that estimate the effects of input-based policies (Wu and Tanaka 2005; Taheripour et al. 2008; Bourgeois et al. 2014). However, other studies draw mixed conclusions. For example, while the fertilizer tax policies implemented in Austria and Sweden have been found to significantly reduce fertilizer application, the fertilizer taxes implemented in Denmark, Finland and Norway did not decrease fertilizer use significantly (Rougoor et al. 2001; Söderholm and Christiernsson 2008; Ahodo and Svatonova 2014). Explanations for the insignificance of the policy in these countries include a low tax rate, the recycling of tax revenue back to farmers, and the interaction of the policy effect with other policies, this insignificance nevertheless raises concern on the general effectiveness of input-based policies. Our results provide further evidence that input-based policies might significantly reduce fertilizer application.

Table 3.3: Estimates of the Long-Term Price Elasticity

		Price				
		Corn	Fertilizer	Labor	Land	Machinery
Quantity	Corn	0.29*** (0.09)	-0.34*** (0.09)	-0.01 (0.01)	-0.14*** (0.02)	0.02 (0.06)
	Fertilizer	0.96*** (0.25)	-0.98*** (0.28)	-0.02 (0.04)	-0.40*** (0.07)	0.60*** (0.19)
	Labor	0.12 (0.21)	-0.08 (0.23)	-0.33*** (0.08)	-0.11 (0.10)	0.48** (0.20)
	Corn Land	0.40*** (0.07)	-0.43*** (0.07)	-0.02 (0.02)	-0.02 (0.05)	0.25*** (0.07)
	Machinery	0.12 (0.13)	0.25** (0.13)	0.05** (0.02)	0.13** (0.06)	-1.27*** (0.22)

All estimated elasticities are constructed using parameter estimates shown in Table D.1 from the fixed effects seemingly unrelated regression. Standard errors are calculated using the delta method, and ***, **, * indicates significance at 1, 5, and 10 percent levels.

We find similar insights with respect to policies that work by changing the relative price of corn (output-based policies); these policies also affect fertilizer application beyond the short-term through the adjustment of quasi-fixed inputs and, especially, land allocation. However the elasticity of fertilizer demand with respect to the price of corn does not increase significantly (as shown later, there is only a small increase in the elasticities) from the short-term to the long-term. Like input-based policies, output-based policies act primarily through the short-term at the intensive margin – i.e., a reduction in the fertilizer application rate.

Our results also confirm that output-based policies that affect the relative prices of corn lead to adjustments in fertilizer application in the short-term and long-term, and are consistent with findings that a high corn price is one of the main drivers of high fertilizer application (Stuart et al. 2014) and high nitrogen loss to the water system (Hendricks et al. 2014). Our findings provide support for the feasibility of the suggested policy of targeting a reduction in fertilizer use through the integration of environmental standards into government commodity program payments. All else equal, a higher compliance cost of corn production means a lower real price received by farmers, and consequently the change in the relative price of corn and soybeans will lead to a reduction of fertilizer use.

Even in the long term, we continue to find that fertilizer application responds similarly to a decrease in the corn price or an increase in the fertilizer price. Hence, in both the short-term and the long-term, output-based (i.e., corn price) policies and input-based (i.e., fertilizer price) policies are equally effective in reducing the application of fertilizer.

3.4.3 Cost-Effectiveness of Policies

Even though the elasticity of fertilizer with respect to fertilizer price and crop price are similar, the cost of input- and output-based policies per unit of abatement differ. Our estimates indicate that input- and output-based policies take effect at the same speed; hence, our analysis on the relative cost-effectiveness of these policies focuses on the magnitude of the cost of the policies and the total effect. The average annual fertilizer application in our sample is 1,828,672 metric tons, the average fertilizer price is $392/metric ton, the average annual production of corn is 21,083,636 metric tons, and the average corn price is $92/metric ton. A 10 percent reduction in fertilizer application with an input-based policy (e.g., a tax on fertilizer) requires a 10.2 percent tax on each unit of fertilizer (i.e., the target reduction divided by the own-price elasticity of fertilizer, 10/0.98). This translates into a total cost of $73,146,880 (calculated as 1,828,672*392*(-10/-0.98)/100). The same 10 percent reduction in fertilizer application via an output-based policy (e.g., a tax on corn production) costs $202,051,512, which is almost three times larger than that of the input-based policy.

These calculations indicate that, given our estimated elasticities, the cost to agricultural producers of achieving a reduction in fertilizer application is smaller with an input-based policy than with an output-based policy. Conversely, if the reduction in fertilizer application is encouraged through a subsidy instead of a tax, the cost to the policymaker of achieving a 10 percent reduction in fertilizer application is smaller if achieved through the input-based policy. These calculations reinforce the idea that input-based policies are generally preferred. As we have discussed, the findings in previous studies that compare input- and output-based policies are mixed. Our results demonstrate that, at least for our study area, input-based policies are superior from a cost-effectiveness point of view. The advantage of the input-based policy may come from the fact that the input-based policy directly targets fertilizer; conversely, an output-based policy targets corn or soybean production, which is ultimately translated into a change in fertilizer application indirectly. It is likely that some of the adjustment induced by the output-based policy is translated into the adjustment of other inputs.

3.4.4 Decomposing Long-Term Adjustments

Two components contribute to the difference between the short- and long-term elasticities: the adjustment of land allocation and the adjustment of capital. We are especially interested in the adjustment of land allocation since it represents the vehicle through which price policies affect fertilizer application at the extensive margin. While the (small) magnitude of these effects can be explained by a small effect of each of these components, it could also be the result of an offsetting effect. We analyze each component to ascertain whether there are any differential effects on fertilizer application via either of these channels. Tables 4 and 5 report the estimates of the components of the long-term elasticity separately.

Table 3.3 shows that less land is used for planting corn when the corn price is lower or when the fertilizer price is higher. Policies directed towards the prices of corn and fertilizer influence land allocation adjustments from corn to soybeans, which further decreases fertilizer application. Table 3.4 shows that a 1 percent decrease in the corn price and a 1 percent increase in the fertilizer price cause a 0.006 percent and 0.007 percent decrease in fertilizer application respectively by decreasing the land allocated to corn. Hence, the magnitude of this extensive margin effect is trivial compared to the intensive margin effects, and the effects of output- and input-based policies are similar in magnitude (at least in terms of the point estimate).

Table 3.4: Estimates of the Long-Term Price Elasticity from Adjustment in Land Allocation

		Price				
		Corn	Fertilizer	Labor	Land	Machinery
Quantity	Corn	-0.008***	0.008***	0.000	0.000	-0.005***
		(0.001)	(0.002)	(0.000)	(0.001)	(0.002)
	Fertilizer	0.006**	-0.007**	-0.000	-0.000	0.004**
		(0.003)	(0.003)	(0.000)	(0.001)	(0.002)
	Labor	0.000	-0.000	-0.000	-0.000	0.000
		(0.002)	(0.002)	(0.000)	(0.000)	(0.001)

All estimated elasticities are constructed using parameter estimates shown in Table D.1 from the fixed effects seemingly unrelated regression. Standard errors are calculated using the delta method, and ***, **, * indicates significance at 1, 5, and 10 percent levels.

A change in either the price of corn or the price of fertilizer also stimulates adjustment of capital, which in turn affects fertilizer use. Table 3.5 shows that the cross-price elasticity of fertilizer application with respect to the corn price related to an adjustment in capital is not significant. The own-price elasticity of fertilizer related to an adjustment in capital is significant, but its magnitude is still small, only -0.009, which indicates that its impact on the reduction of fertilizer application is weak.

3.4.5 Temporal Adjustment Rates of Quasi-Fixed Inputs

Another important dimension to analyze is the time it takes for adjustments to fully take place. Table 3.6 contains estimates of the adjustment rates of the quasi-fixed inputs. As Equation (3.8) indicates, the adjustment rate is the proportion of the total desired adjustment (i.e., adjustment to the optimal level of quasi-fixed inputs) that unravels within a year. Results indicate that the adjustment rate of corn land is -1.17, which means that the entire adjustment in land allocation to the optimal level can be completed in one year; further, this estimate indicates slight over-adjustment as the (absolute) value is greater than 1.

Table 3.5: Estimates of the Long-Term Price Elasticity from Adjustment in Capital

		Price				
		Corn	Fertilizer	Labor	Land	Machinery
Quantity	Corn	-0.002	-0.004*	-0.001*	-0.002*	0.021***
		(0.002)	(0.002)	(0.000)	(0.001)	(0.008)
	Fertilizer	-0.004	-0.009*	-0.002*	-0.004	0.044***
		(0.005)	(0.005)	(0.001)	(0.003)	(0.016)
	Labor	-0.001	-0.002	-0.000	-0.001	0.011
		(0.002)	(0.003)	(0.000)	(0.001)	(0.012)

All estimated elasticities are constructed using parameter estimates shown in Table D.1 from the fixed effects seemingly unrelated regression. Standard errors are calculated using the delta method, and ***, **, * indicates significance at 1, 5, and 10 percent levels.

This rate of adjustment in land allocation may appear to be rapid compared to the findings of other studies, which usually indicate multiple years of dynamic adjustment (Vasavada and Chambers 1986; Lansink and Stefanou 1997). Yet, in the Wabash River Watershed the two main crops – corn and soybeans – are traditionally grown in rotation, making it easy for farmers to switch production between corn and soybeans. This case is different from that considered in other studies; for example, rootcrops and other outputs in Lansink and Stefanou (1997). Furthermore, since our data are county level data, while the adjustment of land allocation could be sluggish for a certain farmer due to reasons such as rotational requirements or contractual restrictions, county-wide adjustments are more flexible because the adjustment only requires some farmers to re-allocate land. When the price of corn or fertilizer changes, the county may achieve the new optimal level quickly once the most responsive farmers adjust their production. The rapid rate of adjustment in land allocation indicates that the extensive margin effects of price policies take place quickly, and so the time required for desirable behavioral changes at a policy-relevant level of aggregation is not a concern.

Table 3.6: Estimated Rates of Adjustment for Quasi-Fixed Factors

	Corn land	Capital
Corn land	-1.17***	0.07
	(0.06)	(0.11)
Capital	0.02	0.13***
	(0.01)	(0.03)

All estimated elasticities are constructed using parameter estimates shown in Table D.1 from the fixed effects seemingly unrelated regression. Standard errors are calculated using the delta method, and ***, **, * indicates significance at 1, 5, and 10 percent levels.

Table 3.6 shows that in contrast to land allocation the adjustment in capital stock is slow. Only about 13 percent of the total desired adjustment is completed in a year, so it requires about 8 years for capital to adjust to its optimal level after a policy-driven shock. This estimate is similar to those found by Chang and Stefanou (1988) and Lansink and Stefanou (1997). However, given that the capital adjustment component in the long-term elasticity of fertilizer is small (i.e., the evolution of capital does not significantly influence the evolution of fertilizer application as revealed by our results), this slow rate of capital adjustment does not substantially impact the time-frame for the realization of the policy goals.

It is important to point out that the rapid adjustment of land allocation and the small difference between the short-term and long-term elasticities indicates that, in our study area, the landscape displays a high speed of adjustment to input- and output-based policies. Therefore input- and output-based instruments are on equal footing, with no instrument prevailing over the other in terms of the time elapsed between implementation and effect. We bear in mind that our study is conducted at a county-level in an area in which corn and soybeans are grown on rotation; both factors explain, in part, this rapid adjustment, and also imply that our findings do not necessarily translate into other environments characterized by different crops or different units of analysis. Hence, our results should not be taken as general indication that speed of adjustment is not relevant for policy assessments.

3.5 Conclusions

Economists often advocate input-based and output-based economic policies to reduce water pollution from fertilizer use. Input-based economic incentives consist of taxing the use of fertilizer or subsidizing a reduction in fertilizer application. Output-based incentives consist of taxing fertilizer-intensive crops (e.g., corn) or subsidizing fertilizer-saving crops (e.g., soybeans). Both types of policies affect fertilizer use by influencing the fertilizer application rate directly in the short-term and/or indirectly through the adjustment of quasi-fixed inputs (i.e., land re-allocation) in the long-term. Though the direct effect occurs in a single year, the indirect effect may require more time if quasi-fixed factors adjust slowly. For policymakers, both the monetary cost and speed of effectiveness are important policy considerations. Hence, a complete assessment of the relative cost-effectiveness of these two types of policies considers both the monetary cost and the speed of adjustment.

Consistent with theory and past research, we find that both input- and output-based policies lead to a significant reduction in fertilizer application, but input-based policies are more cost-effective than output-based policies. In terms of the speed at which they take effect, the two types of policies are similar to each other; in particular, both types of policies take effect rapidly – i.e., from one year to the next. Hence, adjustment in land allocation is not time costly, implying that policies that operate through this channel are not time costly either. One explanation for our result is that, since we focus on the Corn Belt where corn and soybean are only two main crops, land allocation adjustments between corn and soybeans are relatively easy for farmers who typically grow these crops on rotation. We also find that much of the total effect of these policies occurs through changes at the intensive margin (i.e., the reduction in the application rate of fertilizer), while the effect through the extensive margin (i.e., the effects from adjustments of land allocation from corn to soybeans) is small.

Three limits of this study should be mentioned. First, county-level fertilizer application data is not available; instead, we use county level fertilizer sales data. We maintain that, at least in our study area, fertilizer sales data is a good proxy for application data; yet, there is likely some error in measurement. Second, because the temporal dimension in our data is limited because of fertilizer data availability, our analysis assumes static expectation of prices which amounts to a restriction that farmers do not fully consider price uncertainty. Future analysis may relax this assumption. Third, this study ignores the possibility that some farmers may respond to adverse environmental-climate conditions by increasing fertilizer application. Incorporating risk-aversion as a factor underlying fertilizer application may be worthwhile.

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CHAPTER 4 HYBRIDS AND HOUSEHOLD BEHAVIOR: IMPLICATIONS FOR MILES TRAVELED AND GASOLINE CONSUMPTION

4.1 Introduction

The United States government has spent millions of dollars since 2006 encouraging household consumers to purchase fuel efficient vehicles, largely in response to oil price shocks and rising GHG emissions from fossil fuel dependent transportation since 1990 (EPA 2015). The Energy Policy Act of 2005 provided a substantial income tax credit for gasoline-electric hybrids, and over the 2000's decade, gasoline-electric hybrids became nearly synonymous with high fuel efficiency – e.g., the Toyota Prius or Honda Civic hybrid. Calculations by Sallee (2011), for instance, indicate 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, clearly indicating a continued policy focus on increasing the proliferation of alternative-fuel vehicles.[8]

The purpose of these policies is twofold. At a household level, the goal is to reduce gasoline consumption by encouraging households to drive hybrids. At a market level, the proponents of these policies hope to stimulate widespread adoption of hybrids that may otherwise take a relatively long period of time to gain traction in the market; the spread of hybrids could lead to a higher level of fuel saving in the future. It is important to understand whether these policies can be successful in both aspects – in reducing gasoline consumption for households that choose to buy hybrids, and in jump-starting the hybrid car market. Yet, as described by Allcott and Mullainathan (2010), a critical, though sometimes overlooked, aspect of this policy discussion regards the interaction

[8] 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).

between behavioral drivers of demand – e.g., biocentrism, egoism, guilt, and social status – and these two policy outcomes. Reliable policy assessment requires the counterfactual; these non-trivial, and largely unobservable, behavioral factors make the counterfactual elusive. Our interest in this paper is to disentangle several behavioral drivers of hybrid vehicle demand, in order to assess the extent to which certain behavioral motives explain hybrid ownership and driving habits, and to generate insight into the efficacy of these incentive-type policies.

We bear in mind the following points in our assessment of the impact of hybrid ownership on fuel savings. First, for the proliferation of hybrid ownership to lead to (large) reductions in fuel consumption, it should be the case that a household that owns a hybrid will not increase its driving miles to the extent that the fuel savings from driving the hybrid are substantially offset; i.e., there is no (substantial) rebound effect. Otherwise, the proliferation of hybrid vehicles would not lead to the expected reduction in fuel consumption. Second, we focus on both individual and social incentives (pressure) that correlate with hybrid ownership and driving habits. If hybrid ownership was random throughout the population, and it could be observed that the average hybrid driver consumes less gasoline relative to the average non-hybrid driver, a policy designed to encourage hybrid ownership across a larger segment of the population would likely generate a significant reduction in gasoline consumption. Yet, hybrid ownership is not random, and the counterfactual in terms of driving habits for hybrid owners is not known. For example, if a household that purchases a hybrid has biocentric preferences, fuel savings may stem primarily from these preferences and not hybrid ownership *per se*. This situation would imply that continued proliferation of hybrid vehicles may quickly lead only to marginal fuel savings at best, as the preferences of marginal consumers became less biocentric.[9] Given the complexity of these demand drivers, our starting point is the recent theoretical and empirical work linking behavioral and environmental economics (Kotchen and Moore 2007, Allcott and Mullainathan 2010, Allcott 2011, Jacobsen et al. 2012, Sexton and Sexton 2014, Delgado and Khanna 2015, Delgado et al. 2015), which

[9] Assume, for the sake of argument, that consumer preferences are uniformly distributed over a continuous range of biocentrism, such that the endpoints represent zero and complete biocentrism. Biocentrism indicates the extent that households care about the environment.

motivates our perspective that, not only is the choice to buy a hybrid not random, it depends on factors that also affect the driving behavior of households. A major contribution of this paper is developing estimates that allow us to disentangle some of these complex behavioral demand issues, and gain insight into the relationship between hybrid vehicles and fuel consumption.

The socially-oriented behavioral motives also bear important implications for the broader goal of trying to stimulate widespread proliferation of hybrid vehicles in the consumer market. This may generally boil down to social status effects – the desire to maintain one's relative standing among peers, or to adhere to (local) biocentric social norms. Recent research (Narayanan and Nair 2013, Sexton and Sexton 2014, Delgado et al. 2015) has identified these social effects to be an important and statistically significant factor underlying part of the proliferation of the highly visible Toyota Prius. Unlike non-social behavioral factors, the social factors bear important implications for the efficacy of a policy that tries to jump-start the consumer market. On the one hand, the social incentives can increase the speed at which such policies stimulate markets – the policy provides a first incentive, but social incentives quickly kick in to augment the policy. The result may be a rapid proliferation of hybrid vehicles. Yet, on the other hand, the same social incentive creates a potential rebound effect – in order to capitalize on the social value of buying the hybrid, a household has an incentive to drive the hybrid more. The result is the potential to undo, to an unknown extent, the benefits of hybrid vehicle proliferation. We follow previous research and focus exclusively on the popular Toyota Prius to assess the extent to which this socially-driven rebound effect exists, as this focus provides the most plausible means of identifying this social-status driven rebound effect.

We use a matching approach to identify and estimate the average treatment effect of hybrid ownership on treated (i.e., hybrid owning) households. The fact that some factors affect both the household decision to adopt a hybrid and its driving behavior leads to selection bias. This selection may stem from some factors that are easily observed. For instance, since hybrid vehicles are more expensive than conventional-engine counterparts, we expect that individuals with higher income are more likely to drive a hybrid. Standard matching methods constitute a robust means of eliminating bias stemming from these observable effects. Yet, the behavioral demand discussion implies that there are largely unobservable factors, which include personal factors (biocentrism, egoism, guilt, or cost-saving) as well as social factors (social status or social environmental awareness/pressure). These factors are important because they influence both hybrid ownership as well as driving habits; these individuals would likely consume less gasoline in the counterfactual scenario in which they did not own a hybrid. To deal with the selection coming from these factors that are difficult to observe, we develop indicators to measure them indirectly. We require that our matching procedure match exactly on geographic location to ensure that the hybrid and non-hybrid matched pairs face the same social incentives for hybrid adoption. In addition, we include the average MPG rating of all other vehicles in the household in our nearest-neighbor covariate matching set, so as to ensure that matched households have similar underlying preferences for cost saving and environmental preservation. We describe these details more fully in Section 4.4.

We find that, on average, a hybrid household drives more miles per year than the average non-hybrid household. However, this rebound effect is only about 3 percent of the total annual miles traveled, and is insufficient to offset the fuel savings due to the higher fuel efficiency of the gasoline-electric hybrid engine. Therefore, there is a substantial fuel saving generated by hybrid adoption. We do not find evidence that the miles traveled for Prius households are significantly different from non-Prius hybrid households, which indicates that there is not a statistically identifiable social-status driven rebound effect associated with the adoption of the Prius.

4.2 Summary of Related Research

4.2.1 Factors that Influence Hybrid Vehicle Adoption

Recent work has emphasized the importance of behavioral, social, and financial incentives underlying hybrid vehicle adoption. While there certainly may be other factors that correlate with hybrid vehicle adoption, such as income, education, or age (Ozaki and Sevastyanova 2011, Heutel and Muehlegger 2014), such correlates are readily observed and straightforward to control for econometrically. Hence, our discussion focuses on more complex incentives.

Fuel Efficiency Hybrid vehicles are designed to be more fuel efficient than comparable conventional engine vehicles, leading to a reduction in fuel costs. Research (Heffner 2005, Klein 2007) has found that improved gas mileage is a significant factor underlying hybrid adoption, and may be especially important for a household that depends greatly on personal vehicle travel; for instance, a relatively long commute, and/or no easy access to public transportation.

Personal Preference for Environmental Quality There is a growing consensus that a substantial number of consumers value environmental quality, for reasons not limited to altruism, egoism, guilt, or off-setting; see, for example, Kotchen (2005, 2006, 2009), Kotchen and Moore (2007), and Jacobsen et al. (2012). Delgado and Khanna (2015) describe these motives from a general theoretical framework. The relevant insight from these papers is a recognition that consumer preferences for environmentally friendly products – which includes hybrid vehicles – are significant drivers of such consumer demand (Kahn 2007), and that these preferences are largely unobservable and difficult to disentangle (Delgado et al. 2015). Nevertheless, these preferences render hybrid ownership non-random in a population of consumers, and without careful consideration, these differences might lead to substantial bias in treatment parameter estimates.

Openness to New Technology Turrentine and Kurani (2007) and Ozaki and Sevastyanova (2011) find evidence that consumers who adopt hybrid vehicles are those who enjoy pioneering new technology. This characteristic is less frequently discussed as a factor underlying hybrid vehicle adoption; yet, the gasoline-electric hybrid is not a trivial evolution in personal automobiles and is a symbol of new technology and bears substantial uncertainty in terms of reliability and performance.

Rising Gasoline Prices Gasoline prices largely rose over the 2000s decade, and the impact of rising gasoline prices on hybrid adoption has been repeatedly confirmed. Rising gasoline prices have led to an increase in the hybrid vehicle market share in both the United States (Diamond 2009, Beresteanu and Li 2011) and the United Kingdom (Ozaki and Sevastyanova 2011).

Hybrid Vehicle Diffusion Another motive underlying hybrid vehicle adoption that is closely linked to social and behavioral incentives, as well as government program incentives, is hybrid vehicle diffusion into the consumer automobile market. As hybrid vehicles become more commonplace, consumers feel more confident that hybrid technology is reliable and grow more comfortable with the idea of driving a hybrid vehicle. 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; hybrid vehicle diffusion depends on the perceived quality of the new technology. Mau et al. (2008) and Axsen et al. (2009) report similar findings.

Social Norms There is a growing consensus that social factors may be a significant motive behind hybrid vehicle adoption. Hybrid owners may earn positive social status in an environment in which there are social norms that include valuation of environmental amenities. Others may feel social pressure to conform to these social norms. 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. Kahn (2007) finds that people living in a more environmental friendly community are more likely to adopt a hybrid. Research has generated 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, Heffner et al. 2007, Axsen et al. 2009, Sexton and Sexton 2014, Delgado et al. 2015).

Government Sponsored Financial Incentives As mentioned in the introduction, the federal government (and some state governments) have spent large sums of money encouraging household consumers to invest in hybrid vehicles.[10] The general belief is that these incentives are largely effective, though empirical results are not unanimous. Chandra et al. (2010), Ozaki and Sevastyanova (2011), Beresteanu and Li (2011), and Gallagher and Muehlegger (2011) find evidence that government incentives (such as tax

[10] 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.

incentives or traffic policies) significantly impact 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). Identification of the effect of these incentives is difficult given that these incentives are collinear with time trends, are aggregate across a dataset of household individuals, and because the effects may be confounded by consumer self-selection into the hybrid market leading to free-riding on these policies (Chandra et al. 2010). Diamond (2009) does not find that financial policy incentives impact hybrid adoption.

4.2.2 Factors that Influence Household Driving Habits

Personal Preferences and Social Norms The same individual/household and social behavioral factors that influence the decision to adopt a hybrid vehicle may also influence the annual miles traveled by each household. Households that have a stronger motivation to drive a hybrid may have a stronger motivation to drive more or less. For example, while a household that purchases a hybrid because of a long commute tends to drive more than others, a household that purchases a hybrid to reduce travel costs or minimize its environmental footprint may drive less. Particularly, a household motivated to drive a hybrid for social status concerns may have an incentive to drive more in order to capitalize on the social value of the hybrid. Indeed, an interesting aspect that we explore in this paper, is whether social factors also create an incentive to increase driving miles. We describe this in more detail later.

4.2.3 The Rebound Effect

The adoption of energy efficient technology raises concern of a rebound effect, which means that consumers respond to the increased efficiency, in part, by increasing usage (Chan and Gillingham 2015). The proliferation of hybrid vehicles that achieve significantly higher miles per gallon raises concern that hybrid owners may drive more in response to the increased fuel efficiency, relative to the counterfactual situation in which the same household does not own a hybrid. This concern is not without merit, and researchers have been trying to address this issue theoretically and empirically.

Much of the literature addressing the rebound effect focuses on general improvements in fuel efficiency, and not hybrid adoption specifically. Further, much of this research was conducted prior to 2005. Some of these earlier studies use aggregated macro data and estimate rebound effects ranging from 5 percent to 31 percent (Greene 1992; Jones 1993; Haughton and Sarkar 1996). Others use micro 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 of travel distance from an increase in fuel efficiency at the state level in the United States from 1966-2001 and 1997-2001. 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 response of travel distance to the improvement of fuel efficiency by measuring the response of travel distance to a decrease in fuel cost. Specifically, they estimate the rebound effect of travel distance with regard to fuel efficiency by calculating the elasticity of travel distance to a change in fuel cost (per mile). The assumption behind this method is that consumers respond to an improvement in fuel efficiency and to a decrease in fuel price in exactly same way. However, this assumption may not be valid because consumers usually respond less to an increase in fuel efficiency than a decrease in fuel price (Gillingham 2011). With U.S. national time series data, Greene (2012) rejects the null hypothesis that the elasticities of vehicle travel with respect to fuel prices and fuel efficiency are equal and opposite in sign, and while consumers' response to fuel price is significant, their response in travel distance to fuel economy is not. Therefore, a rebound effect measured by the elasticity of travel distance with regard to fuel cost may be overestimated.

Greene (2012) confirms the difference in the rebound effect of travel distance to fuel economy and fuel cost and separates them to estimate the pure rebound effect of fuel economy. However, he still calculates the elasticity of travel distance to a change in fuel economy, and measures the rebound effect at a macro level. Hence, there are two main differences between our study and Greene (2012). First, we pursue a new method, covariate matching, to directly compare the driving distances of households that are same to each other at all characteristics except the fuel efficiency of the vehicle they drive. Through matching households facing the same fuel price, we separate the effect of fuel efficiency from the effect of fuel price. Second, our study is conducted at the household level, which provides a micro level rebound effect (it is not clear the extent to which aggregation to a macro level affects estimates of the rebound effect.)

Another difference between our work and previous studies is that we focus on the rebound effect of an improvement in fuel efficiency from a special type of vehicles, hybrid vehicles, instead of a general improvement in fuel efficiency. Some hybrid vehicles are different from general higher fuel efficiency vehicles because their distinctive look endows them with a special value, a social signaling value, which signals social norms and affects the social status of drivers. The special social signaling value may induce an additional rebound effect, which may differentiate the rebound effect of hybrid adoption from the rebound effect of a general improvement in fuel efficiency.

As far as we know, there are only a few studies that focus on hybrid adoption specifically to measure the rebound effect. de Haan et al. (2006) and de Haan et al. (2007) use a sample of Toyota Prius buyers in Switzerland to investigate whether households switch to the hybrid from a smaller vehicle, and whether vehicle ownership might increase. They do not find evidence to suggest that either of these two rebound effects are significant. Given limitations in their data, they do not investigate whether Prius buyers drive more than non-hybrid owners; this latter effect, however, is more likely according to the literature.

4.2.4 Social Status Driven Rebound Effect

One characteristic of hybrid vehicles is higher fuel efficiency, which may induce a rebound effect of hybrid ownership similar to the rebound effect from a general improvement of fuel efficiency. Some hybrid vehicles, however, have another characteristic: they are instantly recognizable as being fuel-efficient hybrids. This leads to a new kind of rebound effect, which is distinct from a general improvement in fuel efficiency. Because (some) hybrid vehicles are recognizable, the driver is able to signal his/her social awareness, responsibility, and concern for others (Heffner et al. 2005, Heffner et al. 2007, Axsen et al. 2009, Sexton and Sexton 2014, Delgado et al. 2015). This social signal value may motivate the drivers of these hybrids to drive more in order to send signals; this leads to a special rebound effect, a social status driven rebound effect. Identifying the existence of this status signaling rebound effect is important for understanding whether hybrid adoption leads to same degree of fuel saving as a general improvement of fuel efficiency.

However, isolating the social status driven rebound effect is not simple since any change in travel distance coming from hybrid adoption could be the combination of the two rebound effects. Our strategy is to explore the existence of the social status driven rebound effect through comparison of household annual miles traveled for those that drive the Toyota Prius with those that drive other hybrid vehicles. This strategy arises from the fact that the physical look of most hybrid vehicles is not distinct from non-hybrid counterpart vehicles. The Toyota Prius, on the other hand, does not have a non-hybrid counterpart, and further was designed to be visually distinct from all other vehicles available during the 2000s decade. That is, while most hybrid vehicles can only be identified from their non-hybrid counterparts by the hybrid label on the rear of the car, the Prius is instantly recognizable. As is clear from the literature, households are willing to pay for the symbolic benefit of the Toyota Prius in order to signal their environmental status. Several studies quantify the value of this status signal: Sexton and Sexton (2014) calculate this status value as being between \$420 and \$4,200, and Delgado et al. (2015) estimate it to be around \$587.

Given the unique signaling value of the Toyota Prius, if there exists a social status rebound effect driven by this signaling value, we expect to find it when we compare the adoption of the Prius to the adoption of other hybrid vehicles. Conversely, if we cannot find a significant social status driven rebound effect from Prius adoption compared to regular hybrid adoption, we are able to conclude that there is no significant social status rebound effect associated with hybrid adoption that is driven by the signaling value.

4.3 Reduced Form Evidence

Before developing our empirical model, we begin with a brief reduced form analysis to describe the patterns in our data. Understanding these patterns is important for later assessment of the ability of our preferred matching approach to eliminating any covariate imbalance between hybrid and non-hybrid households.

Factors That Correlate With Hybrid Ownership We first explore factors that correlate with hybrid ownership via probit regression of a hybrid ownership indicator on household demographics, the availability of government (federal and state) incentives, local (city-level) gasoline prices, geographic controls, and year fixed effects. The data is described in detail in Section 4.5; we report these results in Table 4.1.

We find that many common stereotypes hold in our data: hybrid owners tend to have relatively high income, have a graduate education, are frequent internet users, and have fewer family members. We find that households that have higher MPG ratings on other vehicles in the household are also more likely to own a hybrid, which suggests consistency in fuel efficiency and environmental preferences within the household.

Table 4.1: Probit Estimates of the Propensity Score of Hybrid/Prius Ownership

	Hybrid Adoption	Prius Adoption
Constant	−4.935*** (0.444)	−1.372 (1.094)
Middle Income	0.069 (0.043)	−0.047 (0.133)
High Income	0.297*** (0.045)	−0.232* (0.136)
High School Degree	−0.230 (0.209)	0.347 (0.796)
Associate's Degree	0.007 (0.204)	0.564 (0.775)
Bachelor's Degree	0.118 (0.204)	0.656 (0.773)
Graduate Degree	0.365* (0.204)	0.872 (0.772)
No. of Vehicles	0.004 (0.022)	0.107* (0.060)
Household Size	−0.067*** (0.016)	0.015 (0.046)
Average Age	0.020*** (0.008)	−0.020 (0.022)
Average Age Squared	−0.0002** (0.0001)	0.0003 (0.0002)
Share of Female Drivers	−0.079 (0.062)	0.134 (0.174)
Internet Usage	0.243*** (0.053)	0.322* (0.169)
Average Vehicle MPG	0.030*** (0.003)	0.027*** (0.006)
Commute Distance	0.0001 (0.001)	−0.0001 (0.002)
Federal Incentive	0.091** (0.046)	−0.077 (0.126)
State Incentive	−0.009 (0.033)	0.076 (0.078)
HOV Lane Access	−0.059* (0.031)	0.030 (0.086)
Gas Price	0.136*** (0.042)	0.217* (0.112)
Urban	0.012 (0.032)	−0.139 (0.092)
Mid-Size MSA	−0.159*** (0.037)	−0.153 (0.098)
Small MSA	−0.187*** (0.039)	−0.143 (0.106)
Not in MSA	−0.234*** (0.049)	0.051 (0.138)
2002 Indicator	0.914*** (0.324)	
2003 Indicator	0.985*** (0.320)	−0.575* (0.341)
2004 Indicator	1.168*** (0.317)	−0.029 (0.312)
2005 Indicator	1.288*** (0.316)	−0.301 (0.308)
2006 Indicator	1.162*** (0.335)	−0.571 (0.434)
2007 Indicator	1.394*** (0.320)	−0.645* (0.333)
2008 Indicator	1.391*** (0.322)	−0.737** (0.349)
2009 Indicator	1.144*** (0.374)	−6.058 (87.334)
Observations	36,780	1,285
Log Likelihood	-5,017.169	-826.755
Akaike Inf. Crit.	10,096.338	1,713.511
Range of support	[0.000,0.458]	[0.000,0.953]

Middle income is defined as income between \$50,000 and \$100,000 per year, and high income is defined as annual household income above \$100,000. The range of support at the bottom of the table indicates the range of support of the estimated propensity score for each model. Statistical significance at the 10, 5, and 1 percent level is denoted with $*$, $**$, and $***$, respectively. In the Prius adoption model, both 2001 and 2002 year indicators are used as the base category because there are too few households in the data that purchased a Prius in 2001.

Table 4.2: OLS Estimates of Annual Miles Traveled for Hybrid/Prius Adoption

	Hybrid	Prius
Constant	1,013.50 (6,218.80)	3,425.52 (35,493.17)
Hybrid/Prius Adoption	914.28*** (341.55)	−800.94 (665.76)
Middle Income	1,284.93*** (168.94)	544.83 (1,167.21)
High Income	2,897.99*** (196.02)	2,591.68** (1,194.54)
High School Degree	−98.15 (630.64)	6,225.19 (5,910.51)
Associate's Degree	932.56 (626.03)	9,140.24 (5,717.48)
Bachelor's Degree	720.07 (630.34)	8,751.38 (5,704.42)
Graduate Degree	796.81 (633.46)	9,200.45 (5,700.19)
No. of Vehicles	7,305.19*** (101.13)	8,288.42*** (524.99)
Household Size	1,304.51*** (70.25)	822.43** (409.35)
Average Age	185.28*** (33.32)	180.98 (193.36)
Average Age Squared	−3.12*** (0.31)	−2.92 (1.78)
Share of Female Drivers	42.50 (273.07)	−310.17 (1,527.74)
Internet Usage	954.46*** (188.98)	−1,109.45 (1,479.80)
Average Vehicle MPG	−30.79** (14.02)	−0.46 (44.96)
Commute Distance	164.16*** (3.94)	190.82*** (19.02)
Gas Price	−1,054.90 (1,588.37)	−7,839.47 (9,023.96)
Urban	−1,826.30*** (148.24)	−1,567.92* (817.35)
Mid-Size MSA	608.97*** (224.62)	787.50 (996.85)
Small MSA	1,155.14*** (224.77)	435.04 (1,078.01)
Not in MSA	2,742.35*** (251.10)	3,227.70** (1,308.28)
Observations	36,780	1,285
State Fixed Effect	Yes	Yes
R^2	0.33	0.43
Adjusted R^2	0.34	0.40
Residual Std. Error	11,846.46	11,184.06
F Statistic	265.99***	14.48***

Middle income is defined as income between $50,000 and $100,000 per year, and high income is defined as annual household income above $100,000. Statistical significance at the 10, 5, and 1 percent level is denoted with $*$, $**$, and $***$, respectively.

Table 4.1 shows that federal tax incentives (see Appendix F for details) are positively correlated with hybrid ownership (Sallee 2011). We do not find that state level incentives are significant, and we find that HOV lane privileges are negatively related to hybrid ownership.[11] We also find that gasoline prices are positively correlated with hybrid adoption, as is MSA city size. Finally, our time dummies reveal an increasing trend in hybrid adoption over time.

In the last column in Table 4.1 we restrict the sample to hybrid owning households, and look for differences between Prius owning households and non-Prius hybrid households. The table reveals that there are few significant differences between Prius households and non-Prius hybrid households. We see that Prius households are less likely to be in the highest income category, have more vehicles, are frequent internet users, and average a higher MPG rating on other vehicles in the household. We suspect that the income effect comes from the presence of luxury hybrids in the dataset: the highest income hybrid consumers are more likely to buy a Toyota Camry hybrid than a Prius.

Factors That Correlate with Annual Miles Traveled In Table 4.2 we report reduced form least squares estimates from the regression of annual miles traveled on the hybrid ownership indicator and control variables. We find that the hybrid indicator is positive and statistically significant, which indicates that hybrid ownership correlates positively with annual miles traveled. The point estimate implies that hybrid owning households, all else constant, drive nearly 915 miles more per year compared to non-hybrid households. The last column in Table 4.2 reveals that there is not a significant difference in annual miles traveled between Prius households and non-Prius hybrid households.

Many other control variables in the hybrid adoption model are significant, and take the expected sign. We see that an increase in income correlates with an increase in annual miles traveled, and that annual miles traveled is increasing with age, though at a decreasing rate. Other point estimates indicate that households in the largest MSAs (the

[11] It is likely that certain state level policies are endogenous to hybrid ownership, which leads to a negative correlation between HOV lane access and hybrid ownership. For example, a state with lower adoption rate of hybrid vehicles may have stronger motivation to provide HOV lane access to hybrids, in order to proliferate hybrid adoption in the state.

base group) average fewer driving miles per year, and households with higher MPG ratings on other vehicles drive fewer miles per year.

As in the probit adoption models, we do not find much significant difference between Prius households and non-Prius hybrid households in terms of annual miles traveled. In this model, we find that annual miles traveled is increasing in income, the number of vehicles, household size, and the length of commute.

The reduced form least squares estimates provide basic information on variables related to hybrid/Prius adoption and annual miles traveled of households. However, our analysis does not entirely rely on these since the reduced forms are limited by the assumed functional form and are not able to incorporate all critical influencing factors (e.g., local social pressure, certain characteristics of vehicles) into the model.

4.4 Model, Identification, and Estimation

4.4.1 Hybrid Rebound Effects

We are interested in understanding the relationship between household ownership of a gasoline-electric hybrid vehicle and annual vehicle miles traveled.

Proposition 1 *Ownership of a gasoline-electric hybrid vehicle leads to an increase in the number of household vehicle miles traveled in a year.*

In line with theoretical insight (Chan and Gillingham 2015), we expect that owners of gasoline-electric hybrid vehicles respond to the increase in fuel efficiency, in part, by increasing annual vehicle miles traveled. Yet, despite this intuition, it is not known to what extent hybrid owning households might increase annual miles traveled, especially when we consider that the adoption of a hybrid may induce a different rebound effect compared to general improvement of fuel efficiency. From understanding the potential for a rebound effect, we can understand the extent to which potential fuel savings from hybrid vehicle adoption may be eroded via behavioral response.

Proposition 2 *There exists a social-status driven rebound effect associated with the Toyota Prius.*

We postulate that a household that owns a Toyota Prius has an incentive to increase its driving in order to fully capture the social-status benefits afforded by the Prius. Research has shown that the Toyota Prius signals environmental social status (Sexton and Sexton 2014, Delgado et al. 2015), and we conjecture that the signaling ability of the Prius is fully realized by maximum driving exposure. This social-status rebound effect has not yet been given direct attention (e.g., status effects are excluded by Chan and Gillingham 2015, p. 141). We believe in the context of hybrid cars this effect may be important. Further, we can understand the degree to which social status effects that serve to increase the proliferation of hybrid ownership may also constitute a hindrance to the efficacy of the incentive policies.

4.4.2 Empirical Framework

We are interested in two potential outcomes:

$$Y_{1i} = \mu_1(X_i) + U_{1i}$$
$$Y_{0i} = \mu_0(X_i) + U_{0i} \tag{4.1}$$

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 hybrid ownership (treatment), X_i is a k-dimensioned vector of observable household-specific factors that influence gasoline consumption, $\mu_j(X_i)\colon \mathbb{R}^k \to \mathbb{R}$ 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. We focus on miles traveled as the outcome, because given fuel efficiency ratings it is straightforward to calculate whether hybrid households consume less gasoline compared to non-hybrid households. This model describes two possible states from which the household chooses – hybrid or non-hybrid – and allows the household to select into a state based on X_i.

Given (4.1), define $\Delta_i = Y_{1i} - Y_{0i}$ to be the effect on miles traveled from driving a hybrid – the treatment effect for household i. From this design, different treatment parameters can be defined; typically, researchers are interested in mean effects. Our interest here is on the mean effect of treatment on treated households:

$$E[\Delta_i|X_i, H_i = 1] = E[Y_{1i}|X_i, H_i = 1] - E[Y_{0i}|X_i, H_i = 1] \quad (4.2)$$

where H_i is a binary indicator for whether or not the household owns a hybrid. That is, we are interested in the average effect of driving a hybrid vehicle on miles traveled for households that own a hybrid. We choose this parameter for the following reason. It is known that identification of the average effect of treatment on any randomly selected household; $E[\Delta_i|X_i]$ requires a full support condition of the propensity score (e.g., Heckman et al. 1998). In our data, this condition fails; we discuss this condition in more detail below, and provide a clear explanation. Rather, our data supports identification of the average effect of treatment on the treated population. Given substantial differences in the populations of hybrid owning (1285 households) and non-hybrid owning households (35,495 households), it is more practical to focus on the average effect of treatment on the treated population.

We can directly estimate $E[Y_{1i}|X_i, H_i = 1]$ using observational data, but not the counterfactual $E[Y_{0i}|X_i, H_i = 1]$. Under the assumption that $E[Y_{1i}|X_i, H_i = 1] \approx E[Y_{0i}|X_i, H_i = 1]$, then a control group of non-hybrid owning households can be used to estimate the counterfactual. The selection bias is given by

$$B(X_i) = E[Y_{1i}|X_i, H_i = 1] - E[Y_{0i}|X_i, H_i = 1] \quad (4.3)$$

and $B(X_i) = 0$ in the event that conditional on X_i there are no differences between the hybrid and non-hybrid households except for hybrid ownership status. Under the structure in (4.1),

$$B(X_i) = E[U_{1i}|X_i, H_i = 1] - E[U_{0i}|X_i, H_i = 1]. \quad (4.4)$$

In other words, the bias will be non-zero if we fail to control all potential unobservables that are correlated with both miles traveled and hybrid adoption.

4.4.3 Identification and Estimation

4.4.3.1 Identification

There are a variety of tools available to deal with observables; Equation (4.4) indicates that our primary concern is in regards to the unobservable factors that may correlate with both hybrid adoption and annual miles traveled. Heckman and Vytlacil (2001a, 2005), Heckman et al. (2006), and related papers describe instrumental variables strategies for identifying and estimating different treatment parameters based on versions of the design in (4.1). Too often in practice, and is the case here, instrumental variables are difficult to obtain.

As we describe in Section 4.5, our data includes numerous (observable) control variables that cover a wide range of factors that correlate with both hybrid adoption and vehicle miles traveled. Despite the richness of data, we remain concerned that there are two unobservable factors that likely influence both hybrid adoption and vehicle miles traveled. The first is household preferences for fuel efficiency and environmental quality, and the second is local social norms. As we describe in Section 4.2, both factors are correlated with both adoption and miles traveled. If we exclude them in the control variables, it is unlikely that the conditional means of these unobservables are either equal across hybrid and non-hybrid states, or both zero, and the bias in (4.4) will not be zero.

In reality, it is very difficult to directly observe households' preferences for fuel efficiency, environmental quality, and the local social norms they face. However, some indicators, combined with the covariate matching method, can be used to capture them indirectly. We precede our analysis by making the following assumptions:

(i) Unobservable household preferences for fuel efficiency and environmental quality is monotonically related to the average miles per gallon of vehicles owned by the household.

The assumption implies that household preferences for fuel efficiency and environmental quality can be captured by the MPG ratings of other vehicles owned by the household. As we will discuss in detail in Section 4.5, the treatment status of a household is defined by one certain vehicle in the household (the criteria used to choose the vehicle is described in that section). We use the average fuel efficiency rating on other vehicles owned by the household in order to ensure that this measure does not depend on the fuel efficiency rating of the vehicle that defines the treatment status of the household. That is, this measure of other MPG ratings is related to the treatment status of the household only through the household's preference for environmental quality. Since only the MPG of other vehicles can be used to measure the household's preference level for fuel efficiency and environmental quality, our analysis is restricted to households that own multiple vehicles.

We contend that this assumption is plausible and not overly restrictive. This assumption requires that for any two households with different degrees of fuel efficiency or environmental preference, the household with a greater preference will have a higher average fuel efficiency rating across vehicles in the household. This allows us to use nearest neighbor matching to control for unobservable preferences for fuel efficiency or environmental quality that influence both hybrid adoption and vehicle miles traveled. In addition, this assumption rules out cases such as a two-vehicle household that owns a Toyota Prius and a Hummer and is characterized by both strong positive and negative environmental preferences.

(ii) Local social norms are constant within a metropolitan area.

This assumption is based on the findings from previous research that households that live in the same area have similar social norms (Kahn 2007, Sexton and Sexton 2014). Through matching households who live in the same metropolitan area to each other, we are able to eliminate the effect of local social norms. We realize that this assumption rules out complex network effects, such as differences in social incentives related to the environment at the place of work, and daily recreation. While these complexities may, in some cases, exist, they are impossible to observe; hence, this assumption places certain restriction on these interactions to make identification tractable, while not completely ruling out social incentives. In our analysis, we consider models that replace *(ii)* with the more flexible assumption:

(iia) Local social norms are constant within a zip code area.

Under *(iia)*, we can allow for variation in social norms across zip codes, but require that social incentives are not heterogeneous within. The zip code area is smaller than the CBSA area, and so matching on zip code relaxes the assumption of homogeneity within the CBSA area though still requiring homogeneity of social norms within the same zip code to maintain tractability.

4.4.3.2 A Matching Estimation Strategy

The fundamental problem of causal inference is that a single household cannot be observed in both hybrid (treated) and non-hybrid (untreated) states at the same point in time (Holland 1986). To address this issue, untreated (control) households can be used to proxy for the counterfactual, and a variety of methods are available to facilitate this comparison. As discussed in Imbens and Rubin (2015), common parametric regression methods depend critically on the functional form restrictions for extrapolation of the counterfactual. A flexible, and more robust alternative is to use the method of matching.

Given our interest on $\tau_{att} = E[\Delta_i | X_i, H_i = 1]$, the method of matching imputes the counterfactual outcome for hybrid drivers nonparametrically via $\hat{Y}_{0i} = \frac{1}{M}\sum_{j=1}^{M} Y_j$ for the M closest matches, in terms of observable characteristics, to household i. We use nearest-neighbor matching, using the Mahalanobis distance metric $A = \left(X_i - X_j\right)' S^{-1}\left(X_i - X_j\right)$ for S being the sample covariance between X_i and X_j, to control for observable factors. In practice, M is selected by the econometrician and we use $M = 1$; Imbens (2004) indicates that one-to-one matching (i.e., setting $M = 1$ so that each treated unit is matched to a single control unit) is the approach with the least bias.

It is well-known, at least anecdotally, that hybrid owners are more likely to have higher income and higher education. Additionally, we might expect that hybrid households are not particularly large (in terms of household members) given that hybrid vehicles are relatively smaller passenger cars. We might also suspect that households that have a longer commute distance to work are more likely to purchase a hybrid as a means of reducing the cost of the commute. Each of these covariates are observable, and including them in our set of matching covariates allows us to eliminate any bias otherwise induced in τ_{att} by differences in these covariates across hybrid and non-hybrid households.

An advantage of the matching estimator, coupled with assumptions *(i)* and either *(ii)* or *(iia)*, is that we can eliminate bias induced by unobservable household green preferences and local social norms by including certain variables into our set of matching covariates. It is possible to explicitly impose an exact match in terms of a specific attribute; asymptotically, discrete and key covariates are exactly matched, though in practice a large sample of control units is required to reliably impose an exact match along a certain dimension (the greater the exact match requirements, the more data that is needed). Given the large size of our set of non-hybrid (control) households, we can reliably restrict our matched households in several key dimensions, and eliminate potential bias from these unobservable factors.

The first dimension on which we require an exact match is the year in which the hybrid was purchased. As discussed in our review of the literature, the hybrid market penetration rate is an important factor impacting hybrid adoption and underlying the proliferation of hybrid vehicles throughout the 2000s decade. Gasoline price and government policy incentives, which vary temporally, are also important factors affecting hybrid adoption. By requiring the hybrid households to match to non-hybrid households that purchased a vehicle in the same year, we can eliminate the effect of the market penetration rate, the effects of temporal changes of gasoline prices and policy incentives on hybrid adoption, as well as other unobservable year factors.

The second dimension on which we restrict our match is the geographical area of residence, defined as either the CBSA or zip code. Restricting the matched households to reside within the same geographic area eliminates any differences in social values that might otherwise confound our estimates of τ_{att}. For instance, certain areas (e.g., San Francisco) are typically regarded as espousing a higher degree of social concern for the environment. By requiring hybrid owners in San Francisco to be matched to non-hybrid owners also in San Francisco, we can eliminate any general effects that are unique to, but common throughout, San Francisco. Exact matching on geographical area also eliminates the effects of spatial variation of gasoline prices and policy incentives. Combined with the exact matching on purchase year, matched households are guaranteed to face the same gasoline price and same policy incentives when they make the vehicle purchase decision.

In our analysis, we consider restrictions at the CBSA level, as well as the zip code level. The former is able to eliminate effects from factors associated with the residential location of the household, and also provides a greater number of matching options in the same matching area which increases the quality of the match for other variables. The latter especially strengthens the location matching, which eliminates the effects of geographical dissimilarities because zip codes are plausibly more homogeneous than CBSAs.[12]

The third dimension over which we require an exact match is the vehicle type or counterpart of each hybrid. Requiring an exact match on vehicle type ensures that our hybrid households are matched to non-hybrid households that purchased a similar sized vehicle (i.e., a vehicle in the same class). To strengthen this matching dimension, we also exactly match hybrid households to those households who did not purchase a hybrid, but purchased a counterpart model of a hybrid. For example, matching a household that purchased a Honda Civic hybrid to a household that purchased a non-hybrid Honda Civic. Following the literature, we match the Toyota Prius, which does not have a counterpart non-hybrid model, with the Toyota Corolla (Sexton and Sexton 2014). Through exact matching on hybrid counterparts, we ensure that matched households are highly similar to each other in vehicle tastes and preferences, with the only difference being whether the vehicle is a hybrid or not.

Other dimensions over which we conduct exact matching include frequency of internet use and household education. We match on frequency of internet use to capture unobservable preferences for new technology. It is important to bear in mind that the NHTS survey was conducted in 2008-2009, and records hybrid purchases over the 2000s

[12] Not all households belong to a CBSA. We consider models in which we classify all households that are not in a CBSA to a common group and match them on state level green plan capacity index, and another model that removes these households from the analysis.

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 is not open to new technology. Finally, our initial attempt was to include education in our nearest neighbor match, but we find via post-match balancing statistics that we obtain a better post-match balance when imposing the exact match on education as well.

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 of the households, including income, household size, number of vehicles, average age of drivers in the household, share of female drivers in the household, commute distance, local green preference capacity index, and average MPG of all other vehicles owned by the household.

4.4.3.3 Identification and Estimation of the Social Status Rebound Effect

To estimate whether there is a social status rebound effect, we restrict the sample to only hybrid vehicles, and to define all non-Prius hybrids to be the control group. Treatment, in this setup, is Prius ownership. We continue to deploy the nearest neighbor and exact matching strategy as described before to deal with both observable and unobservable factors, except that we conduct nearest neighbor matching on education instead of exact matching since exact matching over education no longer improves matching quality. Then, the significance of our matching estimate $\hat{\tau}_{att}$ indicates the existence of a significant social status rebound effect; see, also, Delgado et al. (2015).

4.4.3.4 Failure of the Support Condition Necessary for Identifying the ATE

To further motivate our choice to focus on the ATT, we discuss the potential for identification of causal effects when hybrid ownership is considered as treatment. This discussion is useful for understanding which types of policy assessments can be made in this context. An important result that is described in detail in Heckman et al. (1997) and Heckman and Vytlacil (2005) is that identification of the average treatment effect requires full support of the estimated propensity score of treatment.[13] The average effect of treatment on the treated, on the other hand, only requires the propensity score take values over some interval $(0, p')$ for some $p' < 1$. In essence, identification of the ATT does not require as much from the data; in practice, it is more likely that the ATT is identified even in cases in which the ATE is not. See also Carneiro et al. (2010, 2011).

This point is important because it provides critical insight into the types of causal effects that can be identified with respect to hybrid vehicles and hybrid drivers. Our own probit estimates of the propensity score in Table 4.1 show the range of support being (0.000, 0.458) and (0.000, 0.953). Across many probit models we estimated – that both include and exclude the federal incentive variable as a potential instrumental variable (see the following subsection) – we do not obtain estimates of the propensity score for the hybrid model that have a maximum support that exceeds about 0.55. Given the theoretical econometric conditions, these estimates indicate that identification of an ATE parameter is not feasible (at least given our NHTS sample). In all models we estimate, we do find estimates of the propensity score arbitrarily close to zero, which indicates that the ATT may be identified.

These results, while somewhat disappointing, are both intuitive and informative. If one imagines a stereotypical hybrid household to be relatively high income and high education (this stereotype is also apparent in our NHTS sample), it is certainly possible to find plenty of non-hybrid drivers who match the same demographic characteristics. To use the cliché green/brown terminology, there are plenty of brown consumers who match the demographics of green consumers. This means that comparison of individuals on the basis of observable demographics, for instance through probit regression of the propensity score, does not have sufficient power to satisfy the full support condition. Hence, from these insights, we choose to focus on the ATT; this parameter is more likely to be identified by observational data, and also allows for informed policy assessment via a means of understanding whether existing hybrid owners drive differently from the counterfactual.

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[13] Of course, depending on the chosen estimator, other conditions must be satisfied. To make the current point, we focus only on the support requirement.

4.4.3.5 Why Not an IV Approach?

A related point is the viability of an instrumental variables approach to identification via the tools developed by Heckman and Vytlacil (1999, 2001, 2005). Obviously, any factor that influences hybrid adoption that is correlated with individual, household, or community environmental preferences is not a valid instrumental variable, as the same variable will be correlated with annual miles traveled. Additionally, given that our measurements are at the household level, the more aggregated the measurement of the potential instrumental variable, the more likely the variable is to be a weak instrument (see also Diamond 2009). Given these restrictions, discovery of an instrumental variable is difficult.

Our first instinct was 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 aggregated level and are plausibly exogenous to household vehicle choice. Though these variables are valid, preliminary regressions strongly indicate that these variables are weak and unreliable. The weakness of these instruments comes from the fact that they are aggregated in availability across consumers, and essentially become collinear with gasoline prices, hybrid vehicle penetration rates in the automobile market, and a time trend.[14] It is possible to estimate probit regressions in which the federal incentive measure is positive and significantly correlated with hybrid adoption; see Table 4.1. However, (i) the statistical significance is not stable across samples and model specifications; (ii) is not robust to nonlinear specifications; and (iii) has an average marginal effect of less than 5 percent on the probability of hybrid adoption. Furthermore, direct deployment of the federal incentive as an instrumental variable in an IV-regression of annual miles traveled on hybrid ownership (and controls) generates infeasible coefficient estimates and standard errors, and does not pass standard tests of weak instruments.[15]

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[14] State and local incentives also exist, but these variables are less credibly valid 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. Complete details regarding these variables and regression results can be furnished upon request from the authors.

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

Moreover, economists understand that 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 incentives for these consumers to purchase a hybrid. To be more concrete, in certain communities, hybrid vehicles might bear a negative social stigma, under which many consumers are not willing to purchase a hybrid (for instance, under a government rebate policy). These consumers certainly exist, and it is important to recognize that it is unlikely that their hybrid treatment effect can be identified through typical observational data. Similarly, certain green 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. Research (e.g., Sallee 2011) has shown that the government incentives do significantly correlate with the household decision to buy a hybrid; it is not clear, however, whether green 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 – likely consumers with light-green preferences – as well as being taken simply by green consumers who would have purchased the hybrid regardless (Ozaki and Sevastyanova 2011). It is difficult to know how big is the complier group, and hence whether an instrumental variables approach is a promising empirical strategy.

Instead, our approach is to use a flexible, nonparametric matching approach to eliminate bias from both observable and unobservable factors that influence both hybrid adoption and driving behavior. Given knowledge of the unobservable factors that likely have the largest influence on both the hybrid choice and driving habits (see assumptions *(i)* and *(ii)*), we are able to design a matching setup that eliminates the bias.

4.5 Data Construction and Summary Statistics

4.5.1 Data Construction

The majority of our data comes from the 2009 National Highway Travel Survey (NHTS), conducted nationally 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.

4.5.1.1 The Definition of Treatment

Since we conduct our analysis at the household level, treatment is defined as whether or not the household owns a gasoline-electric hybrid. That is, any household that has purchased at least one brand new hybrid vehicle is considered treated, and any household that has purchased a brand new non-hybrid vehicle is part of the control group. Hence, our analysis is restricted only to households that have purchased at least one new vehicle during the 2000s decade.

We define hybrid status in the following way. For hybrid households, if the households bought only one hybrid, the purchased hybrid is chosen. If a household purchased more than one hybrid, then the hybrid first purchased is chosen because the first hybrid purchase defines the first instant in which the household was hybrid treated. For households that do not own a hybrid, we choose the vehicle that was purchased most recently. The most recent purchase is chosen for three reasons. First, the most recent purchase is the most recent instance in which the household had an opportunity to decide whether to receive treatment or not. Second, given that the NHTS survey was conducted during 2008 and 2009, the most recent purchase corresponds to the purchase time when a household's characteristics are the most similar to its characteristics at the survey time. Third, for matching hybrid households to non-hybrid households who are similar, it is not necessary to match based on all purchases. With a large control group, we have the advantage of choosing the most representative purchase of each household.

4.5.1.2 NHTS Data Sample

Overview Since our focus is on measuring the difference in miles traveled between households who own a hybrid vehicle and households that do not, we include variables measuring hybrid ownership and miles traveled of households, household characteristics, characteristics of all vehicles owned by households, and characteristics of regions in which the households live. All households with incomplete information on these variables are dropped. Since hybrid vehicles are only available in the sample after 2000, to avoid any potential estimation bias from the systematic differences that might exist between households that purchased a hybrid and households that purchased a new car prior to 2000, we limit our study to households who bought at least one new vehicle after 2000. To determine whether a purchased vehicle is brand new or used, we follow the same criterion used by NHTS: when the difference between the purchase year and the model year of a vehicle is less than two years, the vehicle is assumed to have been purchased brand new; otherwise, the vehicle is assumed to have been purchased used.

The NHTS data provides information on whether a specific vehicle is a hybrid vehicle or not; however, in the NHTS survey, gasoline-electric hybrid vehicles are not coded differently from vehicles using some kind of alternative fuel. Since we only focus on electric-gasoline hybrid vehicles, to eliminate vehicles that use alternative fuel 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. The sources for comparison include the Vehicle Make and Model book associated with the NHTS documentation, Edmunds.com, Hybridcars.com, Wikipedia, and previous economic research. Any alternative fuel vehicles that are not found to be gasoline-electrics are dropped.

In addition, we are only interested in vehicles that are used for personal travel and consume gasoline. We include any vehicles classified as automobile/car/station wagon, van (minivan, cargo van, or passenger van), sport utility vehicle, and pickup truck, and drop motorcycle, 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 who own any such vehicle. We also remove all households who own vehicles using diesel, natural gas or electricity, other than motor gasoline.

Several further removals of observations are conducted due to the specific requirements of certain variables. We provide the detailed definitions of some variables included in this study below; the information of the further data removals based on certain variables are also provided in the description of the variable.

Annual Miles Traveled The measure of annual miles traveled by each household comes from the variable BESTMILE in the NHTS survey. Due to the imprecision of perception and memory of respondents, it is difficult to collect precise and reliable information on miles traveled for a whole household in the past whole year. To obtain a reliable measurement of annual miles traveled, NHTS estimates the annual miles traveled for each household via (i) information on each vehicle owned by a household, including self-reported miles traveled, the odometer reading, model year, purchase year, and vehicle type; (ii) information on the primary driver of each vehicle, including the education, age, gender, and working status of the primary driver; (iii) information on the characteristics of each household, including number of persons, number of vehicles, household life cycle classification, and the MSA region in which the household lives; and (iv) miles traveled in the assigned travel day of each household. The most critical sources of information are self-reported annual miles traveled, the odometer reading of each vehicle, and information on the primary driver. When all three sources are available, all are used jointly to construct the estimate of annual miles traveled (72.4 percent of the vehicles in the NHTS survey fall into this category). When some information is missing, only the existing information is used. After estimation, the annual miles estimate is validated via comparison to the odometer reading and self-reported annual miles traveled. If the difference surpasses certain criteria, the annual miles estimate is identified as an outlier. We drop all households for which the BESTMILE estimate is classified as an outlier.

Household Income Household income is a categorical variable, and measures the total income of each household. This variable has 18 different categories, representing intervals of $5,000. For instance, Category 1 indicates annual household income of less than $5,000, and Category 2 indicates annual household income between $5,000 and $9,999. The highest category, Category 18, indicates annual household income greater than $100,000.

Highest Education The NHTS survey records the education level of each person as a categorical variable, taking 5 distinct values. These values from 1 to 5 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 level of education in the household as our measure of household education.

Life Cycle The NHTS survey includes a life cycle variable, that indicates whether the household has one or two heads, children, and whether or not the head(s) are retired.[16] We believe these life-cycle indicators are important correlates of both the hybrid adoption decision and miles traveled.

Internet Usage We include in our analysis an indicator for whether at least one member in the household uses the Internet almost every day. This variable is used to measure both the attitude of the household to new technology, general socioeconomic status, and degree of connectedness. The adoption of a hybrid is affected by the attitude of households towards new technology. If a household is open to new technology, we expect members in that household to use the internet frequently. Since this variable is measured at the person level in the survey, we use the frequency of the person with the most frequent Internet use among all household members, in order to capture the maximum preference to new technology for each household.

Commute Distance to Work Commute distance to work measures the sum of commute distance across all workers in each household. Work commute constitutes mandatory travel, and affects both hybrid adoption and miles driven. We dropped any households with a single family member reporting a commute distance of more than 75 miles.

[16] Specifically, the categories with values 1 to 10 are one adult, no children; 2+ adults, no children; one adult, youngest child 0-5; 2+ adults, youngest child 0-5; one adult, youngest child 6-15; 2+ adults, youngest child 6-15; one adult, youngest child 16-21; 2+ adults, youngest child 16-21; one adult, retired, no children; 2+ adults, retired, no children respectively.

MPG of Other Vehicles To measure the general degree of environmentalism and preference for fuel saving at the household level, we include the average MPG rating of other vehicles. As we have described, it is difficult to measure households' preference for fuel efficiency and the environment; yet, households with stronger environmental preferences and those that care more about fuel costs are more likely to purchase relatively fuel efficient vehicles for all vehicles in the household (see also Table 4.1). Hence, incorporating this variable into our matching analysis allows us to match hybrid households to non-hybrid households that have similar preferences on both fuel efficiency and the environment.

Household Geographic Location The geographic location of households is also correlated with both the hybrid adoption decision and driving habits. For example, households living in a more environmental friendly area would be more likely to buy a hybrid; households living a large metropolitan area may have an advantage of better public transportation and drive less. Additionally, certain states or cities (e.g., California or Seattle; Sexton and Sexton 2014) are known to have a reputation of being more environmentally friendly, which correlates with both hybrid adoption and driving habits. As we have described, matching geographically allows us to control for general spatial influences that may correlate with both hybrid adoption and driving habits.

To control for these correlates, we include several variables to control for these effects. The NHTS survey has several variables that we consider: MSA category, MSA population, and Rail. MSA category measures the metropolitan statistical area of each household, MSA population size measures the size of the MSA in which the household lives, and Rail is a binary variable that measures whether or not the MSA area has rail transportation services available.[17] In addition, we consider a more simple Urban/Rural indicator variable to differentiate households in urban from rural areas.

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[17] Specifically, MSA category takes values 1 if the MSA in which the household lives has a population of 1 million or more, and has a rail system; 2 if the MSA has a population of 1 million or more, but does not have a rail system; 3 if the MSA has a population of less than 1 million; 4 if the household is mot in an MSA. The MSA population variable takes a value of 1 if the household lives in an MSA with fewer than 250,000; 2 for an MSA with a population between 250,000-499,999; 3 for an MSA with 500,000-999,999; 4 for an MSA of 1,000,000-2,999,999; 5 for an MSA of 3 million more; and 6 if the household is not in an MSA.

Basic Household Demographics We also include the number of vehicles in each household, household size, the number of drivers, the average age of drivers, and the number of workers, in order to control for the impact of these household demographics on both hybrid adoption and annual miles traveled. We record the Hispanic status of the household as a binary indicator that equals one if the household self-reports as being Hispanic, and zero otherwise. The race of each household is categorical.[18] We also include the average age of all drivers and the share of female drivers in each household.

Gasoline Price We obtained data on the price of regular grade gasoline from 2000 to 2009 from the Council for Community and Economy Research. The data measures the quarterly gasoline price at the CBSA level, which provides variation across and within years and CBSA regions. We match households via geographic location to gasoline prices. We first match at the city level; any household that cannot be matched to a gasoline price at the city level is matched at the CBSA level; any remaining household is matched into a state average for the gasoline price. For different parts of our analysis, we are interested in both the gasoline price at the time in which the hybrid was purchased, as well as the gasoline price at the time the NHTS survey was taken and annual miles traveled was computed.

Green Plan Capacity Index We also use the Green Plan Capacity (GPC) index from Resource Renewal Institute (Siy et al. 2001) to measure the strength of environmentalism across different regions in which households live as an important control for unobservable factors that may correlated with hybrid vehicle adoption. The GPC index is defined on a 100-point scale, covering 65-indicators, and is calculated for each state in the U.S. It is comprised of four sub-indices: comprehensiveness of the environmental management framework; level of environmental policy innovation; fiscal and program commitment; and the quality of governance. The index is time invariant, varying only over states.

Policy Incentives Incentives from the federal government and state government are also important factors influencing households' hybrid adoptions (Sallee 2011). We obtain

[18] The categories with values from 1 to 8 indicate whether the household members are white, African American, Asian, American Indian or Alaskan Native, Native Hawaiian or Other Pacific, Multiracial, Hispanic/Mexican, and other respectively.

detailed data on these policy incentives from the Internal Revenue Service (IRS), the Alternative Fuels Data Center (AFDC) of the United States Department of Energy, official state statute documentation, and previous economic research (Diamond 2009, Gallagher and Muehlegger 2011, Sallee 2011).

Before 2006, the federal government provided a $2,000 federal tax deduction for all hybrid purchases. The exact benefit for each household depends on the real income tax rate for the household, which we cannot observe. We assume the same tax rate, 25 percent, for all households.[19] Since January 1, 2006, the tax deduction policy was replaced by a tax credit policy. The specific amount of credit that a certain hybrid model receives is based on its fuel efficiency level compared to equivalent gasoline vehicles. The amount of full credit across models varies between $450 and $3,150, and phased out gradually after the manufacturer of the model sold a total of 60,000 hybrids. Federal tax credit incentives for all hybrids from Toyota phased out in 2007, and federal tax credit incentives for hybrid models from Honda phased out at the end of 2008. To obtain a uniform measure of the tax credit across households, we use the weighted mean of tax credits of all hybrids in our dataset at each point in time. The weights of different hybrid models are decided by their proportion across all hybrids models in our dataset, which is used as a proxy of the market share for each hybrid.

State hybrid incentives include income tax credits, sales tax exemptions, tax rebates, and HOV lane access. Detailed information on federal and state incentives, including the specific implementation period, amount, and data sources, are provided in Appendix F.

4.5.2 Descriptive Statistics

Table 4.3 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, while 1,285 households own a hybrid vehicle. Of these hybrid owning households, 696 own a Prius. The distribution of all makes and models of the hybrid vehicles in the sample are provided in Appendix E,

[19] 25 percent is very close to the mean of real incentives benefit Beresteanu and Li (2011) calculated using TAXSIM tax software.

Table 4.3: Descriptive Statistics

Statistic	All Households		Hybrid Households		Prius Households	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Hybrid/Prius Indicator	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	13.92	4.50	15.86	3.47	15.81	3.50
Highest Education	3.77	1.06	4.34	0.86	4.43	0.81
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 Adults	2.10	0.50	2.08	0.47	2.08	0.48
No. of Drivers	2.12	0.54	2.12	0.53	2.14	0.55
No. of Workers	1.21	0.88	1.30	0.87	1.29	0.90
Hispanic	0.05	0.22	0.05	0.22	0.04	0.21
Race	1.29	1.11	1.30	1.14	1.25	1.01
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
Life Cycle	5.98	3.34	5.77	3.32	5.90	3.37
Internet Usage	0.83	0.38	0.94	0.24	0.95	0.22
Commute Distance	14.61	17.73	16.48	18.98	16.20	18.72
Penetration Rate	0.01	0.01	0.02	0.01	0.02	0.01
Gas Price (Purchase)	2.32	0.66	2.61	0.58	2.58	0.59
Gas Price (Survey)	3.51	0.17	3.58	0.20	3.60	0.21
Year Purchased	2,005.49	1.97	2,006.32	1.48	2,006.16	1.54
Vehicle Type	2.05	1.14	1.36	0.77	1.02	0.21
MPG of Other Vehicles	21.21	4.55	23.20	7.34	24.27	8.56
MSA Category	2.49	0.98	2.20	0.98	2.20	1.01
Rail in MSA	0.17	0.38	0.29	0.45	0.31	0.46
Urban	0.70	0.46	0.76	0.43	0.75	0.43
GPC Index	37.71	7.33	38.69	6.99	38.88	7.35
Federal Incentive	881.71	773.85	996.28	805.48	954.74	786.95
State Incentive	96.60	475.38	74.51	488.25	92.99	572.00
Observations	36,780		1,285		696	

Table E.1. In that table, we see that 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, and Ford Escape.

From Table 4.3, we see that the average household drives about 26,636 miles per year; hybrid households drive 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. Not surprisingly, hybrid households average a higher income and education, are more frequent Internet users, average longer commutes, purchased the hybrid in a year/location with higher gasoline prices, and under higher Federal incentives. Further, we see that hybrid households average higher MPG ratings on other vehicles in the household, which provides some indication that hybrid households have uniformly stronger preferences for environmental preservation. We do not find much significant difference between hybrid and non-hybrid households in terms of the other household demographics. In general, these averages conform to the intuition suggested by our review of the literature.

4.6 Covariate Matching Results

4.6.1 Metrics to Assess Balance and Overlap

Prior to implementing our matching and differencing estimation strategy, it is informative to assess overall balance and overlap in the NHTS sample for hybrid and non-hybrid households, and Prius hybrid households and non-Prius hybrid households. The procedures here follow Imbens and Rubin (2015).

The Normalized Difference The first metric we consider for assessing balance is the normalized difference for each covariate, given by

$$\Delta_{ct} = \frac{\mu_t - \mu_c}{\sqrt{(\sigma_t^2 + \sigma_c^2)/2}} \tag{4.5}$$

in which μ denotes the mean, σ^2 denotes the variance, and the subscripts t and c indicate the treated and control samples, respectively. This normalized differences provides a measure of dispersion of the means of the two samples that is unit free. Further, in contrast to the standard t-test for equality of means, the normalized difference is invariant to changes in the sample size. Further, as stated by Imbens and Rubin (2015), the purpose of balance tests is not to directly test the null hypothesis that the two subsamples have the same central tendencies, but rather assess the feasibility of using adjustment methods (e.g., matching or regression) to eliminate biases associated with observable covariates that arise in treatment effect estimation. To estimate Δ_{ct}, one can use sample averages and sample variances.

The normalized difference is in standard deviations. The larger the normalized difference for each covariate, the more difficult it will be to deploy adjustment techniques to adjust for biases. To provide some perspective, normalized difference measures of approximately 0.1 are in line with "what one might expect in a completely randomized experiment" (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

$$\Gamma_{ct} = \log(\sigma_t) - \log(\sigma_c) \tag{4.6}$$

where σ denotes the standard deviation and the rest of notations is as before. This measure can also be calculated from sample standard deviations, and the larger the value of Γ_{ct} for any particular covariate the larger the difference in distributional dispersion. For large values of Γ_{ct}, the more difficult it will be to adjust for biases.

The Fraction of Observations in the Tails of the Opposing Distribution One of the important requirements for different bias adjustment methods (e.g., matching) is sufficient overlap in the distributions of covariates. One way to assess overlap is to determine the fraction of observations in the treated group that lie in the tails of the distribution for the control group. The larger the fraction of observations that lie in the tails of the opposing treatment groups distribution, the more difficult it will be to find a corresponding observation in the opposing group to match to the treated units.

Formally, we calculate this percentage via

$$\pi_t^{\alpha} = \left[1 - F_t\left(F_c^{-1}(1 - \alpha/2)\right)\right] + F_t\left(F_c^{-1}(\alpha/2)\right) \tag{4.7}$$

for significance level α and distribution functions $F(\cdot)$. If we choose $\alpha = 0.05$, we calculate $\hat{\pi}_t^{0.05}$ as

$$\pi_t^{0.05} = \left[1 - F_t\left(F_c^{-1}(0.975)\right)\right] + F_t\left(F_c^{-1}(0.025)\right). \tag{4.8}$$

4.6.2 Pre-Match Assessment of Balance and Overlap

We report the results for our pre-match balance and overlap assessments in Table G.1. For all covariates, we use the full sample of 36,780 observations, of which 1,285 are hybrids and 35,495 are non-hybrids.

It is clear from the table that there are substantial differences between hybrid and non-hybrid households along several important dimensions. We see that 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 0.10. These measures suggest that estimates that do not adjust for these differences are likely to be biased.

The other metrics included in the table indicate that it will likely be 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, which indicates substantial overlap in the distributions of these covariates between hybrid and non-hybrid samples. This is, in part, because of the large number of non-hybrid (control) households afforded to us by the NHTS survey. Through such a large set of non-hybrid households, we are able to carefully identify a close match for each hybrid household.

We report pre-match balance and overlap statistics for the Prius treatment model (hybrid only sample) in Table G.2. For that sample there is fewer significant differences between Prius and non-Prius hybrid samples, pre-match. The largest differences are in terms of education, year purchased, MPG of other vehicles, and vehicle type. With the exception of vehicle type, the other metrics indicate there is likely sufficient overlap to restore adequate balance via matching. We rely on an exact match for vehicle type to restore balance.

4.6.3 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 4.4. In the top two panels, we require an exact match at the CBSA level as given by assumption *(ii)*; the top panel further requires an exact match on vehicle type, and the middle panel further restricts the match to the exact vehicle counterpart. The bottom panel invokes assumption *(iia)* and restricts the match to the zip code level. The rest of the matching is as described previously. Finally, Model 1 includes households that are not located in a CBSA, requiring an exact CBSA 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 matching advantages. Matching on zip code and/or excluding households not in a CBSA are able to strengthen matching on geographical area; matching on the counterparts of each hybrid is able to improve the similarity on all factors influencing households' choice related to brand, style, etc.; matching on CBSA and/or including households not in a CBSA increase the matching options and matching quality of other variables. The combination of all models covers different dimensions that are important in households' driving behavior and hybrid adoption.

Table 4.4: 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		
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 variants. 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, allowing for one matched control unit for each treated unit. CBSA Model 1 includes observations that are not in a CBSA, and Model 2 excludes observations that are not located in a CBSA.

We find that, in most of the models we estimate, hybrid owning households drive more miles per year than households that do not own a hybrid. Our estimates range from just under 400 miles per year to just over 785. To provide more precise interpretation, 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 in the same year, resides in the exact same CBSA (and hence faces the same gasoline prices and social incentives), and has the same household demographics (e.g., income, education, commute distance, etc.). The only insignificant rebound effect comes from the model matching on CBSA, non-hybrid counterparts, and excluding households not in CBSA. Generally, our results are similar across different model specifications, which increases the credence of our estimates.

4.6.4 Is There A Social Status Rebound Effect?

We report our matching estimates of the ATT for the Prius social status driven rebound effect in Table 4.5 for the two CBSA models that match on vehicle type. Due to relatively small sample size of only 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 Prius and non-Prius hybrid households do not drive a significantly different number of miles per year. Hence, despite the anecdotal evidence that the social status signaling ability of the Toyota Prius might create an incentive for Prius drivers to increase driving miles to capitalize on the status signal, we do not find statistical evidence of this behavioral response. Further, we do not find a significant social status rebound effect associated with Prius adoption.

4.6.5 Post-Match Balance and Overlap Assessment

Though our matching estimates are intuitive, the credibility of those estimates as causal effects depends critically on whether the matching procedure was able to restore balance to the covariate distributions. We report post-match balancing statistics for the estimates from Table 4.4 in Tables D.1, D.2, and D.3, and in Table D.4 for the estimates from Table 4.5. 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, and in each case is always below 0.20 (recall that 0.10 is the benchmark for being as good as random). Hence, while there remains a slight distance in terms of this covariate, the match is still very good and it is not likely that this covariate leads to any significant bias in our estimates of the treatment parameter. From these measures, we conclude that there is virtually no cause for concern that our treatment effect estimates are measured with bias.

Table 4.5: Matching Estimates of the Effect of the Prius Premium on Annual Miles Traveled

	Model 1	Model 2
CBSA Level		
Estimate	−669.727	−334.350
Standard Error	581.303	582.087
No. of Matched Hybrids	330	322

The reported estimates and standard errors are Abadie and Imbens (2011) bias-corrected variants. An exact match is required for year of purchase, vehicle type, frequency of Internet use, and CBSA. Matching on other covariates uses nearest neighbor matching using the Mahalanobis distance metric, allowing for 1 matched control unit 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. See text for further details.

4.7 Policy Implications: Hybrid Ownership and Gasoline Consumption

The causal estimates of the impact of hybrid ownership on annual miles traveled has direct implications for policies that seek to reduce gasoline consumption via hybrid vehicle adoption. In this section, we provide some rough calculations as to the average fuel savings accrued on account of hybrid adoption, taking into account the (small) rebound effect we have estimated.

From Table 4.4, the largest hybrid vehicle rebound effect is about 787 miles per year. Given that the average hybrid household in the sample drives 27,914 (Table 4.3), this rebound effect amounts to about 3 percent of annual miles traveled. Table 4.6 shows the average fuel efficiency increase for hybrid vehicles over either non-hybrid vehicles in the same class or to exact non-hybrid counterpart vehicles. In the first case, the average increase in fuel efficiency is 118.5 percent, and in the second case, is 93.4 percent. That is, the average fuel efficiency for hybrids is about double the average fuel efficiency for non-hybrids (either by type or counterpart).

The average annual fuel consumption of a household is calculated by dividing the total annual miles traveled by MPG (fuel consumption = total annual miles traveled/MPG). It is then straightforward to compute a rough estimate of the change in fuel consumption from adoption of a hybrid vehicle.

In the first case, comparing hybrids with all other non-hybrids, we estimate that the highest rebound effect of hybrid adoption is about 787 miles, on average a 2.8 percent increase from original miles traveled, and the corresponding increase of fuel efficiency is 118.5 percent. With the estimates, we calculate the associated fuel savings. Specifically,

$$New\ fuel\ consumption = \frac{New\ VMT}{New\ MPG} = \frac{Original\ VMT\ \times 103\ percent}{Original\ MPG\ \times 218.5\ percent}$$
$$= Orginal\ fuel\ consumption\ \times 47.0\ percent \tag{4.9}$$

which means that the average household that adopts a hybrid decreases its fuel consumption approximately 53.0 percent.

In the second case, we only compare hybrids with their counterpart non-hybrid vehicles. The highest rebound effect of hybrid adoption is about 750 miles, averagely 2.7 percent increase from original miles traveled; the corresponding increase of fuel efficiency is 93.4 percent. The associated fuel savings can be calculated to be 46.9 percent with the same way in Equation (4.9). While this calculation is approximate, the potential fuel savings are substantial. One immediate implication of these calculations is that policies that encourage hybrid vehicle adoption are able to significantly reduce the consumption of gasoline.

Table 4.6: The Increase in Fuel Efficiency from Hybrid Adoption

	All Other Non-hybrids	Non-hybrid Counterparts
Non-hybrid	21.6	24.4
Hybrid	47.2	47.2
Increase in Fuel Efficiency	118.5%	93.4%

Each number reports the average MPG for the vehicles in each category. All other non-hybrid vehicles include all non-hybrid vehicles in our sample; the Toyota Corolla is used as the counterpart for the Toyota Prius.

As discussed earlier, our method is different from the method used in previous studies. First, we separate the response of driving distance to an improvement of fuel efficiency from the response coming from a change in the fuel price. Second, we use a matching method to compare the travel distance of households driving vehicles with different fuel efficiency directly instead of calculating the elasticity of driving distance with respect to fuel economy. To compare our results with findings from previous studies, we transfer our results to be comparable with elasticities. In our case, the fuel efficiency of a hybrid increases 118.5 percent compared all other vehicles and 93.4 compared to the hybrid counterparts. It means that the hybrid fuel costs decrease 54.2 and 48.3 percent, respectively (if we use the same assumption in the previous literature that fuel costs have the equal and opposite effect on travel distance as fuel economy). Correspondingly, with a 100 percent decrease in fuel cost, the travel distance in our cases increase by 5 and 6 percent, respectively. Consistent with the definition of a rebound effect in the literature, the rebound effects in our case are 5 and 6 percent.

Small and Van Dender (2007) find that the rebound effect of driving distance with regard to fuel cost per mile is 2.2 percent in the short term and 10.7 percent in the long term. Hymel et al. (2010) find that the rebound effect is 4.7 percent in the short term and 24.1 percent in the long term. They both measure the response of vehicle travel to the fuel cost per mile, not fuel economy. Greene (2012) measures the response of vehicle travel to fuel economy and does not find a significant rebound effect. Gillingham et al. (2013) find evidence that rebound effects for energy efficient technology do not generally exist, and that any rebound effect that may exist is not enough to offset the environmental gains stemming from the improved efficiency. Our results are generally in line with findings from previous studies, and particularly consistent with the findings of Greene (2012) and Gillingham et al. (2013). With different model specifications, the estimated rebound effect is either not significant or very small.

4.8 Conclusion

We explore households' adoption of gasoline-electric hybrid vehicles and the impact of hybrid ownership on annual miles traveled in order to understand how hybrid ownership impacts fuel consumption. Specifically, we examine two rebound effects: (1) whether households drive more due to the higher fuel-efficiency of hybrids; and (2) if there is a social status driven rebound effect associated with the social signaling value of a hybrid. Our research has important implications for environmental policy related to vehicle miles traveled and gasoline consumption: post assessment of policies encouraging the adoption of hybrids during the 2000's decade; potential impact that policies have on vehicle miles traveled by fully-electric vehicles; and the effects of tightening the Corporate Average Fuel Economy (CAFE) standards which foster proliferation of gasoline-electric hybrids to raise fleet fuel economy. Our analysis critically focuses on issues of identification in light of several behavioral factors that are known to influence both hybrid adoption and miles traveled.

We construct multiple model specifications with different advantages to estimate rebound effects of hybrid adoption. With most model specifications, we find a statistically significant rebound effect due to the higher fuel-efficiency of hybrids: a household that owns a hybrid vehicle drives more miles per year, on average, than an identical household that does not own a hybrid. However, this rebound effect is only about 3 percent of the total annual miles traveled, and is insufficient to offset the fuel savings 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 the Toyota Prius. Generally, we conclude that the rebound effect associated with hybrid adoption is small and hybrid adoption is able to save almost half of current gasoline consumption.

Our ability to interpret these estimates as causal effects rests on whether or not there remain any significant post-estimation differences between hybrid and non-hybrid households. All post-matching balance assessments indicate that there are no remaining differences between the hybrid and non-hybrid samples; hence, our interpretation is causal.

Our results provide an important insight into the effect of government policies that incentivize the adoption of alternative fuel-efficient vehicles and jump-start the alternative fuel car market. In particular, policies that encourage hybrid adoption do lead to fuel savings, despite the non-randomness of households who adopt them and the rebound effect of increased fuel efficiency on vehicle miles traveled. In addition, while certain hybrids are a mechanism to signal social status, we do not find evidence that this same mechanism leads to an alternative form of rebound. Our results also provide a valuable analogue for the effects of policies incentivizing the adoption of fully-electric vehicles or tightening of the CAFE standards.

While the methodology applied in this study appropriately captures the differences between annual miles traveled across households, we have to ignore any intra-household substitution of driving between different vehicles, since miles traveled for each vehicle are aggregated to the household level from the vehicle level. It is likely that hybrid vehicles would be driven more than non-hybrid vehicles inside a hybrid household since the former is more fuel efficient than the latter. However, the possibility of intra-household substitution does not undermine our findings. The substitution of driving from non-hybrid vehicles to hybrid vehicles would only increase the average fuel efficiency of annual driving miles inside the household and induce greater fuel savings.

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CHAPTER 5 CONCLUSIONS

5.1 Summary of Key Findings

The interface between water and agriculture bears important scientific implications. First, water is an important input for agriculture. Irrigation in agriculture is a crucial factor to increase agricultural productivity, and access to water has a substantial impact on local agricultural economic development. Second, agriculture has a substantial impact on water. Irrigation in agriculture constitutes the largest withdrawal of water, which could aggravate water depletion when over-exploitation of water is already severe; agricultural production, especially fertilizer use, is one of the main sources of water pollution in many countries. Studying the specific mechanisms behind the interface of water and agriculture, and identifying the ones that maximize the positive benefit that agriculture can obtain from water and minimize the negative impacts of agriculture on water quantity and quality, are important for achieving agricultural development and sustaining a healthy environment.

My first essay measures irrigation efficiency and explores the most effective policies to reduce groundwater depletion in Mexico. I find that the mechanisms of electricity cost-sharing implemented in many wells have a sizable impact on inefficiency of irrigation application and groundwater depletion. Hence, I conclude that the elimination of cost share mechanisms seems like a more promising policy instrument for groundwater conservation in Mexico. Moreover, irrigation is inelastic to its own per unit cost, and electricity price-based policies may not be able to generate substantial effect in reducing irrigation application. Results also show that well-sharing does not significantly affect groundwater pumping, suggesting either a limited effect of individual pumping on water levels or absence of strategic pumping by farmers sharing the wells.

My second essay compares input- and output-based policies and identifies the most cost-effective policies to reduce fertilizer use and water pollution from agriculture. Results show that both input- and output-based policies lead to a significant reduction in fertilizer application, but input-based policies are more cost-effective than output-based policies. In terms of the speed at which they take effect, the two types of policies are similar to each other; in particular, both types of policies take effect rapidly – i.e., from one year to the next. Hence, adjustment in land allocation is not time costly, implying that policies that operate through this channel are not time costly either.

In my third essay, I find that, on average, a hybrid household drives more miles per year than the average non-hybrid household. However, this rebound effect is only about 3 percent of the total annual miles traveled, and is not large enough to offset the fuel savings from the higher fuel efficiency of the gasoline-electric hybrid engine. Hence, driving a hybrid leads to substantial fuel savings. I do not find evidence that the miles traveled of Toyota Prius households is significantly different from non-Prius hybrid households, which indicates that there is not a statistically identifiable social-status driven rebound effect associated with the adoption of a hybrid.

5.2 Main Contributions

My first essay has four main contributions. First, I theoretically model the existence of cost-sharing externalities, and identify the conditions under which the externality causes higher groundwater extraction. Second, I empirically examine the existence of the cost-sharing externality and quantify its impact on the over-extraction of groundwater. My findings bear important policy implications because cost-sharing is a common issue not only in developing countries but also in developed countries. The (substantial) effect of the cost-sharing externality on the inefficiency of water use indicates the importance for policy to tackle this issue. Third, I compare three policy options faced by the Mexican government and identify the most effective one, which is the elimination of electricity cost-sharing mechanisms in groundwater pumping. Fourth, I address the well-sharing problem, another common issue of groundwater pumping in developing countries, and quantify its impact on over-extraction of groundwater.

My second essay has three main contributions. First, I propose a new dimension of policy assessment, time cost, in assessing economic policies that are directed toward decreasing fertilizer use and water pollution in agriculture. This dimension is important for both policymakers and society, but it has received relatively little attention in previous research. Second, I compare the cost-effectiveness of input and output-based policies to reduce fertilizer use in agricultural production. My findings indicate that while both of them are effective for reducing fertilizer use, input-based policies are more cost-effective.

My third essay has three main contributions. First, I examine the existence of a new rebound effect, a social status driven rebound effect, which is associated with the distinctive outlook and social signal value of the Toyota Prius. Second, I empirically measure the rebound effect induced by the higher fuel efficiency of hybrid, focusing extensively on causal identification and management of omitted variables bias. My method relaxes the assumption used in previous research that consumers' respond to the increase of fuel efficiency and the decrease of gasoline price in the exactly same way. Third, I develop appropriate measurements of subtle characteristics of households, such as a preference on lower travel cost, preference on environmental protection, and social pressure. These characteristics are unobservable and have been obstacles in studying behavioral demand patterns with respect to an increase in fuel efficiency or hybrid adoption.

5.3 Directions for Future Research

My first essay finds that two cost-sharing rules lead to different levels of over-pumping of groundwater, which is interesting and meaningful for policy design. However, the mechanisms behind the differences on the impacts of the two cost-sharing rules, and their potential social welfare implications for different types of farmers are still unknown. If policymakers are informed of these differences, policies could be designed more precisely and their potential impacts on different farmers could be better predicted.

Future research that builds a theoretical model that can provide insight into the mechanism and potential welfare impacts on farmers would be valuable.

My second essay quantifies the cost-effectiveness of policies to adjust agricultural practices, which is essential for policy assessment, but it is only the first step in developing policy that ultimately seeks an improvement in water quality. Beyond measuring cost-effectiveness, another essential portion is measuring the impact of these agricultural adjustments on water pollution. The magnitude of this impact is the key information desired by policymakers. The impact may take a long time to fully appear since nutrient runoff from agricultural production may stay in the water system for several years. That is, the dynamic changes of the impact of the adjustments in agricultural practices on water pollution are important as well. My future research will quantify these dynamic impacts to provide full information for policy design and policy assessment.

My third essay measures the rebound effects of hybrid adoption on miles traveled and finds a significant rebound effect induced by higher fuel efficiency of the hybrid vehicle. According to the literature, the rebound effect may be different in the long-term and in the short-term. Future work measuring dynamic changes in the rebound effects would be interesting.

APPENDICES

Appendix A: Conditions under which electricity cost-sharing distorts marginal cost of pumping

We are interested in identifying conditions under which electricity cost-sharing may reduce the marginal cost of pumping and exacerbate over-extraction. Such a situation occurs whenever $MC_i^{w,s+ws+cs} < MC_i^{w,s+ws}$. Both marginal cost expressions depend upon variables assumed exogenous to the farmer in this study. In particular, the price of electricity (p^{kwh}), the conjectural variation parameter (ρ), the share of the electricity bill paid by farmer i (s_i), and the total amount of water pumped by other farmers in the well ($\sum_{j\neq i} w_j$) are exogenous to the individual farmer.

The conjectural variation parameter captures a farmer's beliefs about other farmers' reaction to his pumping. These beliefs typically emerge from previous experience and are pre-determined (exogenous) relative to the farmer's pumping decision. We consider a range of values of ρ to illustrate the robustness of the distortive effect of cost-sharing on marginal cost. Similarly, cost-sharing rules are established before the beginning of the growing season. Moreover the number of farmers sharing a well and the size of farms were also determined previous to farmers' pumping decisions.[20] Therefore s_i is also exogenously determined in our analysis.

Letting v^{kwh} denote the subsidy per kWh, the difference in marginal cost between farmers without cost share rule and with cost share rule is:

$$MC_i^{w,s+ws} - MC_i^{w,s+ws+cs}$$

$$= [p^{kwh} - v^{kwh}]\big[a + bW + (1+\rho)\big(bw_i - s_i(a + 2bW)\big)\big] > 0. \tag{A.1}$$

With no over-subsidy on electricity cost ($p^{kwh} - v^{kwh} > 0$) and assuming symmetry ($w_i = s_i W$) we can re-write the above condition as:

$$a + bW + (1+\rho)(bs_iW - s_ia - 2bs_iW) > 0 \tag{A.2}$$

which after some algebraic manipulation can be re-written as:

[20] Among the groups that indicated a year of formation in the original survey, less than 10 percent were formed within five years preceding the survey.

$$(a + bW) - (1 + \rho)s_i(a + bW) > 0. \tag{A.3}$$

Since $a + bW > 0$ as defined before, Equation (A.3) implies that

$$MC_i^{w,s+ws} - MC_i^{w,s+ws+cs} > 0$$

if and only if

$$(1 + \rho)s_i < 1.$$

In general the higher ρ, the less likely it is that implementing a cost share rule will reduce marginal cost of pumping. This is to be expected intuitively. When a farmer anticipates that others will significantly increase their pumping in response to an increase in her own pumping, the benefits of cost-sharing vanish.

Table A.1 describes the conditions for increased extraction under cost share. Conditions are depicted for three conjectural variation scenarios: (1) $\rho = 1$, where pumping rates are strategic complements, also known as Loschian conjecture after the model of Loschian competition, (2) $\rho = 0$ where pumping rates are strategically independent, also known as Cournot-Nash conjecture after the model of Cournot competition, and (3) $\rho = -1$, where pumping rates are strategic substitutes, also known as Bertrand conjecture after the model of Bertrand's competition.

Table A. 1: Marginal Cost Change under Cost Share Rules

	$MC_i^{w,s+ws} - MC_i^{w,s+ws+cs} > 0$
$\rho = -1$	$[p^{kwh} - v^{kwh}](a + bW) > 0$, which is always true.
$\rho = 0$	$[p^{kwh} - v^{kwh}](a + bW)(1 - s_i) > 0$, which holds whenever $s_i < 1$. Regardless of the cost share rule, the condition $s_i < 1$ holds for all wells shared by more than one producer.
$\rho = 1$	$[p^{kwh} - v^{kwh}](a + bW)(1 - 2s_i) > 0$, which holds whenever $s_i < 0.5$. When costs are evenly split, $s_i < 0.5$ holds whenever N>2. When costs are divided based on land area, $s_i < 0.5$ holds for all irrigators that operate less than half of the land irrigated by the well; i.e., $L_i < 0.5L$.

Appendix B: Data collection process

The data collection process required two steps. First the enumerators collected the data on the irrigation unit, (e.g., number of farmers sharing the well, crops grown by producers) from an individual familiar with the management of the well. In some cases the respondent is a single individual with well management responsibility while in other cases it is any one of the users or a group of users. The enumerators then asked the respondent(s) to identify a representative individual who produced each of the main crops for the unit. Those identified individuals were interviewed for the crop-specific survey, which was completed for each of the primary crops grown by producers who share the well. Thus, there is one crop-specific survey for each crop-well combination. The crop-specific survey includes questions about inputs, outputs, and prices for each crop.

Cross sectional data was obtained from farmers in a sample of 256 wells. A total of 197 observations contained complete information for our estimation purposes so this is the size of our sample. Irrigation wells are uniformly scattered across the country so they are geographically representative of agricultural groundwater irrigators in Mexico. Regarding the well selection mechanism, a sample was initially drawn based on a national survey of irrigation wells, and the enumerators tried to find those wells from the sample. However, in many cases the irrigation wells that were chosen did not exist. In those cases the enumerators tried to replace the sample well with another well from the same area.

Appendix C

Table C. 1: Coefficient Estimates for Input Demands (water, fertilizer and other inputs)

	Estimates
Water equation	
Constant	-39896.6 (33315.0)
Output quantity	547.6** (247.6)
Interaction of land area and output quantity	-97.5*** (35.4)
Land area	3208.5*** (394.9)
Quadratic term of output quantity	2.1** (0.9)
Interaction of quadratic land area and output quantity	1.0** (0.5)
Dividing electricity bill by share of land area	16456.9** (8114.8)
Dividing electricity bill evenly	25801.5*** (8515.8)
Number of farmers sharing a well	279.0 (316.5)
Soil type	6566.6 (5629.1)
Climate type	12315.7 (14850.1)
Depth of well	42.8 (54.8)
Age	-227.6 (419.2)
Education	4078.8 (4436.3)
Share of fruit and vegetable	3834.3 (11379.4)
Own price elasticity of water	-0.06** (0.02)
Fertilizer equation	
Constant	2059.1 (8825.2)
Output quantity	-167.5** (66.2)
Interaction of land area and output quantity	8.3* (4.9)
Land area	417.3*** (96.9)
Quadratic term of output quantity	0.2 (0.2)
Interaction of quadratic land area and output quantity	-0.04 (0.07)
Dividing electricity bill by share of land area	-73.9 (1862.8)
Dividing electricity bill evenly	-154.4 (2643.8)
Number of farmers sharing a well	62.7 (96.0)
Soil type	358.1 (855.8)
Climate type	-7899.0 (5075.5)
Depth of well	2.0 (7.1)
Age	62.9 (71.9)
Education	-530.0 (1352.6)
Share of fruit and vegetable	3007.5 (3707.5)

Table C.1. Continued

	Estimates
Other inputs equation	
Constant	-15245.0 (13229.9)
Output quantity	66.5 (60.3)
Interaction of land area and output quantity	7.1 (4.5)
Land area	1517.7*** (116.2)
Quadratic term of output quantity	-0.9*** (0.3)
Interaction of quadratic land area and output quantity	-0.2*** (0.1)
Dividing electricity bill by share of land area	-796.3 (2009.3)
Dividing electricity bill evenly	-6010.8** (2759.0)
Number of farmers sharing a well	-62.7 (74.6)
Soil type	-581.0 (2091.5)
Climate type	7362.3 (6421.6)
Depth of well	35.4* (21.1)
Age	170.3 (165.9)
Education	307.1 (1778.8)
Share of fruit and vegetable	2305.2 (4497.1)
R^2 (Water equation)	0.741
R^2 (Fertilizer equation)	0.592
R^2 (Other inputs equation)	0.862
Observations	197

Robust standard errors are in parentheses. Asterisk (*), double asterisk (**) and three asterisk (***) denote that variables are significant at 10%, 5%, and 1% respectively.

Appendix D

Table D. 1: Seemingly Unrelated Regression Parameter Estimates

	Coefficient	Standard Error
A11	2722.86***	784.21
A12	-2095.62***	531.96
A13	-314.06	560.50
A22	1446.34***	418.06
A23	132.51	424.32
A33	4210.31***	974.66
B11	136.19	481.69
B12	-994.10*	515.60
B22	4930.27***	1283.33
C11	-2281.58***	351.14
C12	9.65	517.65
C21	1600.72***	278.40
C22	-1087.95***	372.86
C31	535.11	477.22
C32	-1120.01**	467.65
O11	18.90***	4.86
O21	-3.54	2.56
O31	4.86*	2.62
P11	-0.76***	0.09
P12	-1.28***	0.40
P21	-0.15**	0.06
P22	0.66***	0.22
P31	-0.01	0.06
P32	0.20	0.22
R11	2810.18***	356.24
R21	-1080.62***	275.05
R31	10.62	280.00
S11	-15.00***	1.64
S21	7.06	7.16
V11	-1326.01***	193.97
V21	846.18***	307.03
M11	-1.21***	0.06
M12	0.07	0.11
M21	0.02	0.01
M22	0.09***	0.03

The regression includes fixed effects. ***, **, * indicates significance at 1, 5, and 10 percent levels. The letter name for the parameters corresponds to the matrix names given in Equation (3.5), and the subscript notation refers to the element position (row, column) in that matrix. The order of netputs is corn, fertilizer, labor and the order of quasi-fixed inputs is corn land and capital.

Appendix E: Additional Descriptive Statistics

Table E. 1: Summary of Makes and Models for Hybrid Vehicles

Make	Model	Number	Percent
Cadillac	Escalade	1	0.1
Chevrolet	Tahoe	19	1.5
Chevrolet	Silverado	2	0.2
Chrysler	Aspen	3	0.2
Ford	Escape	59	4.6
GMC	Yukon	10	0.8
Honda	Civic	176	13.7
Honda	Accord	41	3.2
Lexus	LS 600hl	3	0.2
Lexus	GS 450h	9	0.7
Lexus	RX 400h	25	1.9
Mazda	Tribute	1	0.1
Mercury	Mariner	13	1
Nissan	Altima	16	1.2
Saturn	Vue Green Line	8	0.6
Toyota	Camry	133	10.4
Toyota	Prius	680	52.9
Toyota	Highlander	86	6.7
Total		1285	100

The data in this table come from two sources: IRS http://www.irs.gov/uac/AlternativeMotor-Vehicle-Credit-1 and http://www.cars.com/go/advice/Story.jsp?section=buy and subject=tax and story=taxCredit. Further, when there is difference in the credit amount across different model years for a certain hybrid model, we use the credit amount of the most recent model year before 2009. Also, when there is difference in the credit amount across different types of hybrid within a certain model, we use the mean of the credit amounts.

Appendix F: Federal and State Hybrid Adoption Incentives

Table F. 1: Summary of Ongoing Federal Tax Credits for Hybrid Vehicles (after 1/1/2006)

Make	Model	Credit Amount
Cadillac	Escalade	$2,000
Chevrolet	Malibu	$1,300
Chevrolet	Tahoe	$2,200
Chevrolet	Silverado	$450
Chrysler	Aspen	$2,200
Dodge	Durango	$2,200
Ford	Escape	$2,475
GMC	Yukon	$2,200
GMC	Sierra	$450
Mazda	Tribute	$2,475
Mercury	Mariner	$2,475
Nissan	Altima	$2,350
Saturn	Aura	$1,300
Saturn	Vue Green Line	$1,550

Table F. 2: Summary of Phased out Federal Tax Credits for Hybrid Vehicles (after 1/1/2006)

Model	Purchase Date	Credit Amount
Toyota Prius	1/1/2006 - 9/30/2006	$3,150
	10/1/2006 - 3/31/2007	$1,575
	4/1/2007 - 9/30/2007	$787.50
	10/1/2007 -	$0
Toyota Camry	1/1/2006 - 9/30/2006	$2,600
	10/1/2006 - 3/31/2007	$1,300
	4/1/2007 - 9/30/2007	$650
	10/1/2007 -	$0
Toyota Highlander	1/1/2006 - 9/30/2006	$2,600
	10/1/2006 - 3/31/2007	$1,300
	4/1/2007 - 9/30/2007	$650
	10/1/2007 -	$0
Lexus GS 450h	1/1/2006 - 9/30/2006	$1,550
	10/1/2006 - 3/31/2007	$775
	4/1/2007 - 9/30/2007	$387.50
	10/1/2007 -	$0
Lexus RX 400h	1/1/2006 - 9/30/2006	$2,200
	10/1/2006 - 3/31/2007	$1,100
	4/1/2007 - 9/30/2007	$550
	10/1/2007 -	$0
Lexus LS 600h	1/1/2006 - 9/30/2006	$1,800
	10/1/2006 - 3/31/2007	$900
	4/1/2007 - 9/30/2007	$450
	10/1/2007 -	$0
Honda Civic	1/1/2006 - 1/1/2008	$2,100
	1/1/2008 - 6/30/2008	$1,050
	7/1/2008 - 12/31/2008	$525
	1/1/2009 -	$0
Honda Accord	1/1/2006 - 1/1/2008	$1,300
	1/1/2008 - 6/30/2008	$650
	7/1/2008 - 12/31/2008	$325
	1/1/2009 -	$0
Honda Insight	1/1/2006 - 1/1/2008	$1,450
	1/1/2008 - 6/30/2008	$725
	7/1/2008 - 12/31/2008	$362.50
	1/1/2009 -	$0

Table F. 3: Summary of State Level Incentives for Hybrid Vehicles

State	Amount	Start Date	End Date
Income Tax Incentives			
Colorado	$6542*	7/1/2000	12/31/2010
Louisiana	$500*	1/1/1991*	7/9/2009
New York	$2,000	1/1/2001*	12/31/2004
Oregon	$1,500	1/1/1998*	12/31/2009
South Carolina	$630*	6/1/2006	12/31/2009
Utah	$1720*	2001*	12/31/2005*
West Virginia	$3750*	7/1/1997	6/30/2006
Sales Tax Incentives			
Connecticut	$1500*	10/1/2004	10/1/2008
Washington D.C.	$3294*	4/15/2005*	Not yet expired
Maine	$625*	1/1/1997	12/31/2005
Maryland	$1,000	7/1/2000	7/1/2004
Maryland	$1,500	7/1/2004	5/20/2010
New Mexico	$750*	7/1/2004	6/30/2009
New York	$240*	1/1/2000	5/28/2005
Washington	$2,015	1/1/2009	7/31/2009
Washington	$73	8/1/2009	12/31/2010
HOV Lane Access			
California		8/10/2005*	6/30/2007
Colorado		3/1/2008	Not yet expired
Florida		2003	9/30/2017
New York		3/1/2006	9/30/2017
Utah		9/1/2006*	12/31/2010
Virginia		6/30/2006*	7/1/2011
Rebate Incentives			
Illinois	$1,000	7/15/2007	10/1/2008
Pennsylvania	$500	11/29/2004	3/6/2010
Testing Exemptions			
Idaho		2008	Not yet expired
Maryland		2005	9/30/2012
Nevada		5/31/2007	Not yet expired
Personal Property Tax Incentive			
Michigan	$32	7/26/2002	12/31/2012

The * indicates that the value comes from previous studies.

<u>Appendix G: Pre-Match Balancing and Overlap Assessments</u>

Table G. 1: Pre-match Balancing and Overlap Assessment – Hybrid Treatment

	Hybrid Households		Non-Hybrid Households		Normalized Difference	Log Diff. of Std. Dev.	% Hybrid in Tails	% Non-Hybrid in Tails
	Mean	Std. Dev.	Mean	Std. Dev.				
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
No. of Vehicles	2.353	0.646	2.353	0.642	0.001	0.006	0.734	0.732
Household Size	2.617	0.985	2.696	1.128	-0.074	-0.136	0.048	0.066
No. Adults	2.075	0.467	2.100	0.505	-0.051	-0.079	0.065	0.076
No. Drivers	2.125	0.534	2.116	0.544	0.015	-0.018	0.055	0.090
Hispanic	0.051	0.219	0.052	0.222	-0.007	-0.014	0.949	0.948
Race	1.304	1.140	1.291	1.106	0.011	0.031	0.928	0.923
Average Age	53.315	12.852	53.310	14.098	0.000	-0.093	0.026	0.087
Share of Female	0.500	0.209	0.511	0.229	-0.052	-0.088	0.083	0.087
Life Cycle	5.773	3.318	5.991	3.340	-0.066	-0.007	0.339	0.301
No. Workers	1.296	0.869	1.210	0.877	0.098	-0.010	0.219	0.248
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
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
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
Vehicle Type	1.358	0.770	2.079	1.148	-0.737	-0.400	0.822	0.623
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

Table G. 2: Pre-match Balancing and Overlap Assessment – Prius Treatment

	Prius Households		Non-Prius Households		Normalized Difference	Log Diff. of Std. Dev.	% Prius in Tails	% Non-Prius in Tails
	Mean	Std. Dev.	Mean	Std. Dev.				
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
No. of Vehicles	2.368	0.655	2.336	0.635	0.049	0.030	0.724	0.745
Household Size	2.575	0.957	2.667	1.016	-0.094	-0.060	0.045	0.053
No. Adults	2.079	0.478	2.071	0.454	0.017	0.052	0.069	0.061
No. Drivers	2.138	0.545	2.109	0.520	0.055	0.048	0.078	0.056
Hispanic	0.045	0.206	0.058	0.233	-0.060	-0.123	0.955	0.942
Race	1.249	1.006	1.368	1.278	-0.104	-0.239	0.922	0.944
Average Age	54.474	13.063	51.945	12.469	0.198	0.047	0.086	0.041
Share of Female	0.503	0.201	0.496	0.218	0.036	-0.080	0.073	0.095
Life Cycle	5.898	3.372	5.625	3.250	0.082	0.037	0.341	0.338
No. Workers	1.295	0.898	1.297	0.834	-0.003	0.074	0.237	0.197
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
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
Year Purchased	2006.161	1.541	2006.497	1.396	-0.229	0.099	0.057	0.022
MPG of Other Vehicles	24.273	8.558	21.933	5.309	0.329	0.477	0.089	0.051
Vehicle Type	1.023	0.213	1.754	0.975	-1.035	-1.520	0.989	1.000
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

Appendix H: Post-Match Balance Assessments

Table H. 1: Post-match Balancing Assessment for CBSA and Vehicle Type Matching Model – Hybrid Treatment

Covariate	Model 1		Model 2	
	Normalized Difference	Log Diff. of Std. Dev.	Normalized Difference	Log Diff. of Std. Dev.
Household Income	-0.028	0.063	-0.036	0.067
Education	0.000	0.000	0.000	0.000
No. of Vehicles	0.082	0.152	0.078	0.149
Household Size	0.049	0.072	0.051	0.080
No. of Drivers	-0.031	0.147	-0.028	0.150
Hispanic	0.013	0.026	0.009	0.017
Race	0.061	0.170	0.057	0.165
Average Age	-0.052	0.028	-0.049	0.028
Share of Female	0.029	0.266	0.030	0.262
Life Cycle	0.003	-0.029	0.012	-0.026
No. of Workers	-0.080	0.024	-0.083	0.026
Internet Usage	0.000	0.000	0.000	0.000
Commute Distance	0.080	0.206	0.074	0.191
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
Year Purchased	0.000	0.000	0.000	0.000
MPG of Other Vehicles	0.176	0.301	0.167	0.302
MSA Category	-0.006	-0.000	-0.005	-0.003
MSA Size	0.015	-0.012	0.011	-0.010
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
Vehicle Type	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 4.4. An exact match is required for household education, frequency of Internet usage, year of hybrid purchase, vehicle type, 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 4.4 and text for further details.

Table H. 2: Post-match Balancing Assessment for CBSA and Counterpart Matching Model – Hybrid Treatment

Covariate	Model 1		Model 2	
	Normalized Difference	Log Diff. of Std. Dev.	Normalized Difference	Log Diff. of Std. Dev.
Household Income	0.189	-0.079	0.145	-0.030
Education	0.000	0.000	0.000	0.000
No. of Vehicles	0.067	0.119	0.052	0.109
Household Size	-0.023	-0.004	-0.035	-0.006
No. of Drivers	-0.152	0.009	-0.161	-0.005
Hispanic	-0.099	-0.159	-0.102	-0.158
Race	-0.050	-0.019	-0.040	0.008
Average Age	0.010	0.006	0.017	-0.004
Share Female	-0.047	0.034	-0.048	0.051
Life Cycle	-0.138	-0.003	-0.129	0.003
No. of Workers	-0.042	-0.075	-0.055	-0.079
Internet Usage	0.000	0.000	0.000	0.000
Commute Distance	-0.084	-0.075	-0.097	-0.087
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
Year Purchased	0.000	0.000	0.000	0.000
MPG of Other Vehicles	0.067	0.200	0.051	0.211
MSA Category	-0.010	-0.022	0.000	-0.015
MSA Size	-0.039	0.022	-0.028	0.014
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
Counterparts	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 4.4. 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 4.4 and text for further details.

Table H. 3: Post-match Balancing Assessment for Zip Code and Vehicle Type Matching Model – Hybrid Treatment

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

Post-match normalized difference and log ratio of standard deviation statistics for the matched estimates reported in Table 4.4. 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 4.4 and text for further details.

Table H. 4: Post-match Balancing and Overlap Assessment for CBSA Level Matching Model – Prius Treatment

Covariate	Model 1		Model 2	
	Normalized Difference	Log Diff. of Std. Dev.	Normalized Difference	Log Diff. of Std. Dev.
Household Income	-0.205	0.146	-0.246	0.207
Education	0.041	0.101	0.004	0.135
No. of Vehicles	0.132	0.119	0.136	0.124
Household Size	-0.180	-0.065	-0.180	-0.072
No. of Drivers	0.013	0.189	0.007	0.174
Hispanic	0.187	0.426	0.189	0.426
Race	-0.041	0.023	-0.041	0.023
Average Age	0.184	0.171	0.173	0.163
Share Female	0.001	0.225	0.010	0.211
Life Cycle	-0.005	0.065	-0.021	0.060
No. of Workers	-0.190	0.165	-0.169	0.153
Internet Usage	0.000	0.000	0.000	0.000
Commute Distance	-0.069	0.076	-0.068	0.068
Penetration Rate	0.046	0.046	0.047	0.037
Gas Price (Purchase)	0.084	0.052	0.068	0.032
Gas Price (Survey)	-0.019	0.004	-0.003	-0.003
Year Purchased	0.000	0.000	0.000	0.000
MPG of Other Vehicles	0.127	0.111	0.101	0.124
MSA Category	-0.004	0.005	0.008	0.017
MSA Size	-0.006	0.018	-0.003	0.023
Rail in MSA	0.012	0.001	0.006	0.001
Urban	-0.095	0.080	-0.128	0.122
GPC Index	-0.022	0.107	-0.035	-0.096
CBSA	0.000	0.000	0.000	0.000
Vehicle Type	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 4.5. 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 text for further details.

VITA

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