How Markets, Policies and Consumers Influence the Transition to Clean Energy

A DISSERTATION

SUBMITTED TO THE FACULTY OF THE

UNIVERSITY OF MINNESOTA

BY

Bixuan Sun

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS

FOR THE DEGREE OF

DOCTOR OF PHILOSOPHY

Jeffrey Apland, Steve Miller

August 2018

Acknowledgements

First, I would like to thank my advisors Prof. Jeffrey Apland and Prof. Steve Miller for their support throughout my PhD study. Without their guidance and encouragement, I would not have completed my thesis, gained knowledge and research experiences, and most importantly found my passion. I specifically want to acknowledge Prof. Miller's significant contribution to Chapter 1. I also want to thank Prof. Stephen Polasky and Prof. Gabe Chan for offering me great advice on my thesis proposal and final draft as committee members. My gratitude also goes to Prof. Marc Bellemare, Prof. Joe Ritter, Prof. Jay Coggins, Prof. Paul Glewwe, and Prof. Frances Homans, who spent the time to provide comments and discuss questions about my research. In addition, I would like to thank the staff in the department of applied economics, including Elaine Reber, Karen Routhe, Ellen Carlson, Jenna Mead, Gary Cooper and Linda Eells, for assisting me with questions I have and making my progress in the PhD program as smooth as possible.

I want to express my sincere appreciation towards my wonderful friends in the program: Tomoko Utsumi, Huichun Sun, Ashwini Sankar, Soomin Lee and Mariana Urbina. My PhD study became colorful because of their friendship and camaraderie, and I am grateful to have been on this amazing journey with them.

I would not have completed my thesis and PhD degree without the tremendous support from my family. I sincerely thank my parents, Rui Sun and Xiangping Wang, for always being my rock and role models even from thousands of miles away. I greatly appreciate my mother-in-law, Jeannette Carmichael, and my aunt and uncle, Jake and Michelle Gage, for always being there to support my study and my life.

Last but not the least, I want to thank my wonderful husband, Justin Sun, from the bottom of my heart, for always supporting my dreams, for encouraging me to push boundaries and for sharing the good times and helping me through the hard times, during my PhD study and in my life.

Abstract

Climate change poses fundamental threats to human populations and ecosystems. Transitioning to a cleaner and more sustainable energy system is central to combating climate change while ensuring universal energy access. However, the transition to clean energy is not free of obstacles. The major players in the energy system, including producers, regulators and consumers, have diverse objectives. My dissertation studies how these players shape the transition to a cleaner, more efficient energy system. The first chapter models the strategic interactions between the dirty producer and the clean producer in the transition to clean technology, showing that the incumbent dirty producer can use market power to deter the entry by the clean producer and suppress R&D investment in clean technology. The impacts of tax and subsidy on peak pollution stock, as well as social welfare, are also analyzed. In the second chapter, I develop a theoretical model of consumers' responses to energy efficiency policies, and present empirical evidence that shows a negative direct rebound effect for Energy Star dishwashers and a potentially positive direct rebound effect for Energy Star air conditioners. Negative rebound effects can amplify energy savings, while positive rebound effects can offset energy savings from using more efficient technologies. The third chapter uses machine learning methods to study how the impacts of solar rebate programs vary with the presence of other solar policies and demographic characteristics in the U.S. The results show a positive average treatment effect of solar rebate programs with significant heterogeneity. Important factors explaining the heterogeneity include Renewable Energy Portfolio, residential electricity rate and year of installation. Relationships between treatment effect and important explanatory factors display significant non-linearity. These findings suggest that legislative goals are more likely to support rebate programs than other types of solar policies, and certain solar market characteristics are indicative of high program effects.

Table of Contents

List of Tables

List of Figures

How Markets, Policies and Consumers Influence the Transition to Clean Energy

Introduction

Climate change poses fundamental threats to human populations and ecosystems. The 2014 report issued by the Intergovernmental Panel on Climate Change, an international scientific organization, warns that climate change threatens to have "severe, wide-spread and irreversible impacts globally" unless we undertake substantial mitigation efforts. Transitioning to cleaner and more sustainable production systems, such as energy and manufacturing systems, is central to combating climate change. However, the transition to clean production technologies is not free of obstacles. The major players, including producers, regulators and consumers, have diverse objectives. My dissertation seeks to analyze the impacts of these players' actions on the transition, using empirical evidence from the energy industry. Understanding these impacts will help us design better policies that facilitate a smoother and faster transition to cleaner and more sustainable production systems.

The first chapter is a theoretical analysis of the impact of dirty producer's market power on the transition to alternative clean production technology. Specifically, this chapter develops a model to study the strategic interactions between the dirty producer and the clean producer in the transition process. In this model, the dirty producer begins with a lower cost of production while the clean producer has higher cost of production initially but can achieve a reduction in cost through investment in new technologies. Both players observe each other's actions and develop optimal strategies to maximize their profits in the long run. The analysis shows that the incumbent dirty producer can use its market power to deter entry of the clean producer if the initial clean technology knowledge stock is sufficiently low. High market power increases barriers to entry and lowers investment in clean knowledge capital. A tax on dirty production has greater marginal effect on peak pollution level compared to a subsidy on clean production, but the latter generates higher social welfare.

This chapter makes two contributions to the existing literature on technological transition and market power. First, the model allows each producer to observe the other's plans and react strategically, while previous studies usually assume producers set their optimal plans in the beginning and do not interact strategically. Second, the model accounts for the urgency of climate change by assuming non-exhaustible resources. Previous studies usually show that the driving force behind technology transition is the depletion of polluting resources. However, as climate change becomes an increasingly urgent issue, the clean technology transition may arrive well before the depletion of polluting resource reserves. In the context of energy industry, the results in this chapter reflect the dynamic nature of the current energy system and highlight the significance of policy interventions to the energy transition.

After laying the theoretical foundation for the importance of policy intervention, in the second chapter I theoretically and empirically examine the effectiveness of a residential energy efficiency program[1]. In 2012, the residential sector accounted for 21% of total primary energy consumption and generated about 20% of total carbon emissions in the U.S. (U.S. Energy Information Administration, 2015). By adopting energy efficiency measures, households can reduce their energy bills and help protect the environment. However, as energy efficiency measures reduce the amount of energy consumed for certain household tasks (e.g., a load of laundry), those tasks become relatively cheaper. Consequently, consumers might alter their energy using behavior (e.g., doing more loads of laundry), which affects the total energy savings and carbon reduction. The change in energy savings due to this behavioral response is referred as the "direct rebound effect". This chapter seeks to examine the existence and size of the direct rebound effect in the Energy Star appliance program, which was put forth by the U.S. Environmental Protection Agency (EPA) to promote energy efficient products and buildings. I first develop a theoretical model that shows the sign of the direct rebound effect depends on the type of energy service. I then present empirical evidence which shows a negative direct rebound effect for Energy Star dishwashers and a potentially positive direct rebound effect for Energy Star air conditioners. The former amplified energy savings, while the

[1]This chapter is published as "Sun, B. (2018). Heterogeneous direct rebound effect: Theory and evidence from the Energy Star program. Energy Economics, 69, 335-349. https://doi.org/10.1016/j.eneco.2017.11.025".

latter offsets energy savings from using more efficient technologies.

The contribution of this chapter to the literature on energy rebound effects is threefold. First, I develop a household choice model that considers both the purchase decision of Energy Star appliances and the decision on the frequency of use. The model shows that the type of appliance influences both the sign and size of the direct rebound effect. Previous work usually focuses on a single appliance and does not consider whether the rebound effect differs across different appliances. Second, lacking the data on appliance usage, previous studies usually use consumers' responses to changing energy prices to approximate direct rebound effects. Such approximation is only accurate if certain unrealistic assumptions hold, such as the assumption that the investment in energy efficiency is reversible. I avoid this issue by utilizing the 2009 Residential Energy Consumption Survey conducted by the U.S. Energy Information Administration, which collected data from 12,083 households and recorded the frequency of using their home appliances. This rich dataset allows me to estimate the direct rebound effect as the impact of improved efficiency on the frequency of using the appliances. Third, the purchase of an energy efficient appliance is a household choice, and unobserved factors influencing that decision (e.g., environmental awareness) might also affect the frequency of use. I use an instrumental variable, the state-level sales of Energy Star appliances at the time of survey, to address this sample selection problem and provide a more accurate estimate of the direct rebound effects.

In addition to energy efficiency programs, renewable energy policies also play an important role in mitigating greenhouse gas emissions. In recent years, the U.S. has experienced impressive growth in its solar photovoltaic (PV) sector. Federal and state governments have played large roles in promoting residential solar installations through a myriad of policies, including regulatory frameworks and financial incentives. There is a growing body of literature examining the determinants of increased residential solar PV capacity, but these studies usually focus on one policy or state, and do not consider the interactions among policies and demographic factors. In reality, policies are usually implemented simultaneously and might influence each other, hence isolating one policy's effectiveness is unlikely to be informative. In addition, the order in which different policies are enacted often matters. For example, financial incentives for residential solar PV systems likely only work if certain regulatory ground rules are set in advance.

In the last chapter I empirically examine the heterogeneous effectiveness of rebate programs at promoting residential solar energy systems in the U.S. Specifically, I seek to understand how the treatment impact varies by the existence of other policies, and how different types of subpopulation benefit from solar rebate programs differently. I combine inverse propensity score weighting with causal forests, a novel machine-learning tool, to analyze a zip-code level panel dataset spanning nine years (2007-2015) for 36 states in the U.S. The results show a positive average treatment effect of solar rebate programs with significant heterogeneity. Regulatory frameworks, such as Renewable Energy Portfolio, and solar market characteristics, such as residential electricity rate and cost of installation, play important roles in explaining the heterogeneity. Important demographic factors include county level median house value and median income level. Analysis also shows significant nonlinearity in the relationships between treatment effect and these factors.

The major contribution of this chapter is to provide a better understanding of how program effects vary by other policy and non-policy factors. It is likely that we do not have a complete understanding of the interactions among policies and demographic factors. Empirically testing a model with a set of predetermined interaction terms might omit some important relations and yield misleading results. Causal regression forests offer data-driven approaches to partition data into subgroups that differ in the magnitude of policy impact. These machine-learning tools can fully explore the conditions in which solar rebate programs perform well (or not well) and how to effectively target sub-populations to increase policy impact. In addition, I estimate the impacts of residential solar policies based on a panel dataset from a large number of states, whereas previous studies mostly focus on California or a smaller region in the U.S.

In sum, my dissertation aims to provide a better understanding of how producers, regulators and consumers influence the transition to clean energy. Understanding the behavior of these groups can help us design better policies to support and accelerate the transition.

Chapter 1. Market Power and the Transition to Clean Technology

Abstract

This paper examines how an incumbent "dirty" producer's market power impacts the transition to an alternative clean technology. Using a dynamic Stackelberg model, we characterize the strategic interactions between the dirty producer (leader) and the clean producer (follower). Specifically, we derive the optimal feedback strategies and the sub-game perfect equilibrium that arises in the absence of resource constraints. We show the incumbent dirty producer uses its market power to deter entry by the clean producer and to suppress investment in clean technology. Policy interventions, such as a tax on dirty production and subsidies for clean investment and production, can reduce peak and long run pollution levels by lowering the entry barrier and stimulating investment in clean technology. Using numerical simulations, we demonstrate that taxes have a larger marginal effect on pollution but clean production subsidies generate higher social welfare.

Keywords: market power, dynamic game theory, pollution

1 Introduction

The continued use of polluting energy sources and production technologies pose threats to people and ecosystems at both local and global scales. Greenhouse gases are of particular concern: the Intergovernmental Panel on Climate Change (IPCC) 2014 report warns that global warning threatens to have "severe, wide-spread and irreversible impacts globally" without substantial mitigation efforts. A specific concern among climate scientists is that the climate system may reach a "tipping point" which triggers a series of environmental disasters (Russill & Nyssa, 2009). The tipping point concept was first introduced in the context of melting Arctic sea ice (Lindsay and Zhang, 2005; Winton, 2006; Holland et al., 2006), and climate scientists have since identified similar concerns across the whole climate system (Lenton et al., 2008; Hansen et al., 2007, National Research Council, 2002). These tipping points have also made their way into economic analyses of climate change (Acemoglu et al., 2012; Weitzman, 2009; Stern, 2013).

In response to these and related threats, many countries have begun to reduce their reliance on fossil fuels. Despite those efforts, increased use of alternate energy sources in the production of goods and services faces at least three key economic obstacles. First, fossil fuels currently dominate the global primary energy supply due to their low current costs of production. Second, those fossil fuel costs are likely to stay low for the foreseeable future: while exhaustability could eventually drive fossil fuel prices upward, known reserves of key resources are large. Finally, producers using fossil fuel-based technologies are incumbents in many markets, and may be able to exert market power to deter investment in and transition to cleaner production technologies. It is the last issue of market power on which we focus our attention: how does the market power of dirty, incumbent producers affect investment in and transition to cleaner technologies as well as pollution, and how might policy interventions counteract those effects?

To answer these questions, we build on two existing areas of research. One branch, beginning with Nordhaus et al. (1973), examines the effects of a clean backstop energy source (with constant marginal cost and no capacity constraint) on transition. Subsequent work studies optimal investment in clean energy capital in both a social planner (Fischer et al., 2004) and competitive market framework (Tsur and Zemel, 2011; Amigues et al., 2015). A complementary body of research examines the role of market power in entry deterrence and investment. A Stackelberg leader-follower structure is appropriate when: (1) the leader has lower production cost due to greater physical or knowledge capital (Fudenberg and Tirole, 1983; Basu, 1995; Van Damme and Hurkens, 1999); (2) there exist asymmetries in information or uncertainty, with the better informed firms acting as leaders (Spencer and Brander, 1992); or (3) transactions take place via long term contracts (Bloem et al., 2007). Many polluting, energy-intensive industries exhibit one or more of the preceding characteristics, inviting analysis in a Stackelberg framework. Examples include energy production (Powell and Oren, 1989), mineral extraction (Wan and Boyce, 2014), and electricity wholesale markets (Mansur, 2013), as well as energy-hungry industries such as semiconductor manufacturing (Cho et al., 1998) and telecommunications (DeMiguel and Xu, 2009).

This paper extends these two lines of inquiry by examining how an incumbent dirty producer's market power affects the speed of investment in clean technology, the rate of clean production, and the costs of avoiding environmental tipping points. Specifically, we analyze a dynamic Stackelberg game in which a dirty producer (leader) and a clean producer (follower) compete in a common output market. The leader initially controls the whole market and has a lower production cost.

The follower has a high initial marginal cost of production but may invest in knowledge capital to lower production costs, eventually giving the follower a cost advantage.[2] If the pollution stock generated by the dirty producer's emissions reaches a critical threshold, an environmental disaster occurs. Using our model, we derive and analyze the equilibrium feedback strategies (i.e. production and investment levels) for both producers and the resulting equilibrium paths of production, clean knowledge capital, and pollution. We then examine the impact of market power, defined as the dirty producer's first mover advantage and the ability to influence market price, by studying how feedback strategies and the equilibrium transition paths are affected by the dirty production cost and elasticity of market demand. Finally, we compare the use of three policy instruments for keeping pollution levels below the critical environmental threshold.

Our approach differs from prior work in several key ways. First, many prior studies assume the incumbent producer relies on a depletable resource, resulting in either rising prices or a total production constraint (Powell and Oren, 1989; Tsur and Zemel, 2011; Amigues et al., 2015). In contrast, we adopt the convention of Acemoglu et al. (2012) and treat the inputs of the polluting sector as non-exhaustible. The justification for this approach is two-fold: first, the exhaustibility constraint is unlikely to be binding before either environmental disaster occurs or the transition to new technologies is complete; and second, it allows us to focus on the effect of market power on the speed of transition. Second, we solve for equilibria in feedback strategies rather than the open-loop strategies used in Powell and Oren (1989). Open-loop strategies in a Stackelberg game can be time-inconsistent (He et al., 2009), because players are assumed to adhere to their initial plans, while in reality firms usually observe the behavior of their opponents and may react strategically. In contrast, the feedback strategies we employ are time-consistent and the resulting equilibria we identify are subgame perfect. Finally, we introduce and analyze potential policy solutions for addressing both types of market failure present in the model: market power and environmental externality.

Our results indicate the incumbent dirty producer can use its market power to deter entry of the clean producer if the initial clean technology knowledge stock is sufficiently low. As in earlier work, entry deterrence takes the form of increased production by the dirty sector to depress prices. However, in cases when the clean producer eventually enters, it does so due to declining clean production

[2] We consider technological change resulting from investment only; we do not consider learning-by-doing in which production costs decline with cumulative production.

costs alone; resource exhaustibility assumed in other work plays no role. Further, comparative statics show that high market power, characterized by low dirty production cost and inelastic market demand, increases barriers to entry and lowers investment in clean knowledge capital. Together, these results demonstrate how market power leads to inefficient production and investment choices, which are likely to compound through their effect on pollution levels. From a policy perspective, we find that a tax on dirty production has larger marginal effects on the peak pollution level during the transition than a subsidy on clean technology investment or production. However, a subsidy for clean production yields higher social welfare because it simultaneously addresses inefficiently low aggregate production and environmental externality that arises due to market power. Consistent with that intuition, we also identify cases in which it is socially optimal for a policy maker to subsidize clean production beyond what is required to keep pollution levels beneath a critical threshold.

The remainder of the paper is organized as follows. Section 2 presents the Stackelberg framework. Section 3 derives the optimal feedback production strategies for both producers and the optimal feedback investment strategy for the clean producer. Section 4 illustrates the impact of market power on the transition using comparative statics on dirty production cost and demand elasticity. Section 5 discusses environmental damages from dirty production and compares policy interventions that can help prevent an environmental disaster. Section 6 concludes and discusses possible extensions to the current analysis. A summary of notation and proofs of propositions are provided in Appendix A.

2 General Framework

In order to examine how market power of an incumbent, polluting producer influences the transition to cleaner production, we analyze a continuous-time model of production and Research and Development (R&D) with two producers. The dirty producer chooses production x_t so as to maximize discounted profits over an infinite horizon, while the clean entrant chooses both production y_t and R&D investment I_t with the same objective. The two firms produce perfect substitutes and compete in a common output market with linear inverse demand $P(q) = \alpha - \beta q$ $(\alpha, \beta > 0)$ which depends only on the total production level $q = x + y$. Both producers take into account of their influence on the market price through this inverse demand function.

The two producers use different production technologies, which result in different production costs and levels of pollution. Both firms face constant marginal costs of production with no cost to adjusting production quantities, so that each produces if and only if the marginal profit from the first unit of production is positive (if marginal profits are zero we assume the indifferent firm will not produce). The dirty producer has fully developed technology and sufficient capital such that production incurs a constant marginal cost c^x. We ignore capital depreciation and maintenance cost in the dirty producer's infrastructure because it does not affect the major dynamics in the model. In the clean sector, the constant marginal cost of production C^y is initially very high, but declines linearly with knowledge capital K until hitting a lower bound.[3] Specifically, the clean producer's marginal cost depends upon knowledge capital K as follows:

$$C^y(K) = \begin{cases} M - AK & (0 \leqslant K \leqslant \frac{M-c^y}{A}) \\ c^y & (K > \frac{M-c^y}{A}). \end{cases},$$

Here M is the maximum clean production cost with no capital stock, A measures the level of capital efficiency, and c^y is the lower bound on clean production cost. Higher capital efficiency implies a larger reduction in production cost for the same amount of capital increase. To increase knowledge capital and thereby lower production costs, the clean producer may invest at rate I_t, resulting in R&D costs $f(I) = \gamma I^2$. Investment affects knowledge capital additively, and we assume that capital does not depreciate, such that the equation of motion for the clean capital stock is

$$\dot{K}_t = I_t,$$

with $K_0 = 0$.

To focus our attention on how market power affects entry and the transition to clean production, we make additional assumptions about how the marginal costs of the two producers are related. Specifically, we assume $M \gg c^x > c^y$, such that initial production costs for the clean producer are high enough that the dirty producer is the sole participant in the market, but that enough investment in knowledge capital will give the clean producer a cost advantage.

To reflect market power of many dirty producers, we assume the dirty producer has a first-mover

[3] Note that capital for the clean firm reduces production cost and has no effect on production capacity, since the clean firm has constant marginal costs.

advantage, resulting in a Stackelberg game. As the Stackelberg follower, the clean producer takes the dirty firm's production rate as given and chooses both production and investment. As leader, the dirty producer takes into account the effects of its production choice on market price, as well as the production and investment decisions in the clean sector. Both firms make their decisions with complete and perfect information. We restrict attention to feedback strategies which are functions of the state variable K_t alone and do not depend explicitly on time. These characteristics of feedback strategies make them time consistent, which means the strategies given the level of state variable are the same at any time t.

With these assumptions, we can write down the optimization problems faced by each producer. The clean producer chooses investment I_t and production y_t in response to the dirty producer's announced production rate x_t so as to maximize the present value of profits (with discount rate r) over an infinite horizon:

$$V^F(K_0) = \max_{y_t, I_t \geqslant 0} \int_0^\infty e^{-rt} \left[P(x_t + y_t) y_t - C^y(K_t) y_t - f(I_t) \right] dt$$

subject to:

$$\dot{K}_t = I_t.$$

The value function of the clean producer (i.e., the follower), denoted as $V^F(K_0)$, is the discounted profit at time zero, which depends on the initial clean knowledge capital K_0. Solving the optimization problem gives the feedback clean investment rate $I(K|x)$ and clean production rate $y(K|x)$ as the functions of the announced dirty production rate x.

As the Stackelberg leader, the dirty producer incorporates the clean producer's reaction functions into its optimization problem and solves for the optimal production rate $x(K)$. Hence, the dirty producer's optimization problem is:

$$V^L(K_0) = \max_{x_t > 0} \int_0^\infty e^{-rt} \left[P(x_t + y(K_t \mid x_t)) x_t - c^x x_t \right] dt,$$

subject to:

$$\dot{K}_t = I_t(K_t|x).$$

$V^L(K_0)$ is the dirty producer's value function. The solution to this problem gives the optimal feedback strategy for the dirty producer $x^*(K)$, which in turn gives us the optimal clean investment rate $I^*(K)$ and clean production rate $y^*(K)$. The strategies $I^*(K)$, $y^*(K)$ and $x^*(K)$ constitute a time-consistent Stackelberg feedback equilibrium.

Before analyzing this model, we briefly note that pollution does not enter into this basic model setup. We assume that, in the absence of any corrective policy, the damages from pollution can be approximated as entirely external to either producer. In Section 5, when we consider policy instruments, we introduce pollution stock and associated damages to the model.

Appendix A.1 provides a summary of notation and assumptions on functional forms used in this section.

3 Stackelberg Equilibrium Feedback Strategies

In this section, we derive the optimal feedback strategies for both the dirty and clean producer as the functions of clean capital stock K. Because both Stackelberg players have perfect information, the optimal strategies are derived using backward induction from the steady state, which occurs after the clean producer reaches the lower bound in its production cost. We begin by characterizing the steady state and then derive the strategies at higher levels of production cost for the clean producer.

3.1 Steady State With Joint Production

In the steady state, both producers have constant production cost. There are no dynamic considerations for either producer in this stage because R&D investment cannot lower the clean producer's production cost further, and clean knowledge capital remains at $K = \frac{M-c^y}{A}$. As a result, both production decisions are static problems, and the clean investment rate is zero. First order conditions indicate the optimal production rates in the steady state ($K = \frac{M-c^y}{A}$) are:

$$x^*(K) = \frac{\alpha + c^y - 2c^x}{2\beta}, \tag{1}$$

$$y^*(K) = \frac{\alpha - 3c^y + 2c^x}{4\beta}. \tag{2}$$

Whether the clean producer controls the majority of the market in the steady stage depends on the relative size of the dirty and clean production cost and the market demand parameter α. If $5(c^x - c^y) > (\alpha - c^x)$, then the clean producer has a higher production rate in the steady state, and vice versa.

3.2 Transition to the Joint Production Steady State

In the transition to the steady state, both firms produce and the clean follower invests in K until C^y reaches its lower bound c^y. The optimization problems faced by both firms in this stage are no longer static but can be solved using standard methods. Proposition 1 characterizes the resulting optimal feedback strategies:

PROPOSITION 1: *When the clean capital stock K is in the range of* $(\frac{3M-\alpha-2c^x}{3A}, \frac{M-c^y}{A})$*, the clean sector invests and produces simultaneously. Optimal production for the dirty (clean) producer linearly decreases (increases) in K, while optimal investment rate in clean knowledge capital first increases in K and then gradually decreases in K until it reaches 0 at* $K = \frac{M-c^y}{A}$.

The proof of Proposition 1 is presented in Appendix A.2. As clean knowledge capital accumulates, the cost advantage gradually shifts from the dirty sector to the clean sector, hence the optimal level of x decreases in K and the optimal level of y increases in K. The speed of investment reflects the shadow value of clean knowledge capital, which first increases and then declines to zero. As shown in the proof, the shadow value depends on two factors: clean production and the time remaining to reach the steady state. At higher levels of clean production, any reduction in the clean production cost generates higher instantaneous profit, hence the shadow value of capital increases (i.e. the "profit effect"). On the other hand, additional capital has zero worth once clean production reaches its lower bound. As the clean producer approaches the steady state, there is less time for him to enjoy the benefit of cost reduction from capital investment, hence the shadow value declines (i.e. the "future capital effect"). At the beginning of the transition, the steady state is far in the future and the positive instantaneous profit effect outweighs the negative future capital effect. As the steady state approaches, the negative future capital effect grows to dominate. Hence, we see the investment rate first increase and then decline to zero.

The feedback strategies in Proposition 1 are strictly interior solutions, i.e. $I > 0$ and $K > 0$, and so apply only when the capital stock is in the range $\frac{3M-\alpha-2c^x}{3A} < K < \frac{M-c^y}{A}$ (see Appendix A.2).

3.3 Strategies Prior to Clean Production

Before the clean producer enters the market, the dirty producer acts as a monopoly producer, though the clean producer may still invest in R&D in preparation for later production, and the dirty firm may alter production decisions so as to deter entry by the clean firm. Since the clean producer will not produce if the marginal profit from the first unit of clean production is negative, this phase is defined by the condition that $C^y(K) \geq P(x)$, where $P(x)$ is the market price arising if only the dirty firm produces at its announced level. As the Stackelberg leader, the dirty firm can thus deter entry by choosing x to be large enough that $C^y(K) \geq P(x)$.

For sufficiently small values of K, the dirty firm can simply produce at monopoly levels and that level of production is enough to keep the clean firm out of the output market. The monopoly level of production is defined by first order conditions for the dirty firm's (static) problem when there is no possibility of entry. Those conditions yield dirty production $x_0 = \frac{\alpha - c^x}{2\beta}$ and a corresponding market price of $P_0 = \frac{\alpha + c^x}{2}$. In order to ensure a positive production for the monopoly dirty producer, $P_0 > c^x$ must hold, which requires $\alpha > c^x$. The dirty firm produces at this monopoly level and the clean firm does not enter as long as $C^y(K) \geq P_0$.

If the clean producer has invested enough in R&D so that $C^y(K) < P_0$, the dirty firm has the option to increase production to drive down the market price and keep the clean firm from producing. As noted above, in order to deter entry, the dirty firm only needs to choose production large enough to ensure $C^y(K) \geq P(x)$. Since that level of production must be larger than the optimal monopoly level x_0, if it is optimal for the dirty firm to deter entry, it will increase production until $C^y(K) = P(x)$ so that the clean firm's marginal profits from the first unit of production are zero and the clean firm would not enter the market. Any further increases in production have no effect on entry and would only reduce the dirty firm's instantaneous profits. Hence after $C^y(K)$ reaches the monopoly market price P_0 (i.e. $K = \frac{M - P_0}{A}$), the feedback dirty production rate can be derived from setting the market price equal to the clean production cost:

$$x^*(K) = \frac{\alpha - M + AK}{\beta}. \tag{3}$$

Such entry deterrence persists until it is optimal for the leader to allow the clean firm to enter the market, which occurs when $K = \hat{K} \equiv \frac{3M - \alpha - 2c^x}{3A}$. Proposition 2 summarizes this deterrence behavior:

PROPOSITION 2: *When the clean production cost $C^y(K)$ reaches the dirty producer's monopoly price P_0, the leader (i.e. the dirty producer) initiates entry deterrence to keep the follower (i.e. the clean producer) from producing until $K = \frac{3M-\alpha-2c^x}{3A}$, and the path of the market price coincides with that of the clean production cost as the clean producer invests in R&D.*

The proof of Proposition 2 is presented in Appendix A.3. The intuition is that because the leader always moves first and the entry decision of the follower is reversible and costless, the leader needs to constantly deter the entry of the follower until the threat of price reduction is no longer credible. The threat ceases to be credible once the leader's profits are higher under joint production than under deterrence, which occurs once $K = \frac{3M-\alpha-2c^x}{3A}$.

Even though the dirty producer's entry deterrence keeps the clean producer from producing, it may still be optimal for the clean producer to invest in R&D to drive down clean production costs for entry at a later time. Proposition 3 states the conditions under which the clean firm will undertake such R&D investment in advance of entry:

PROPOSITION 3: *The clean producer will start investing before producing when the initial capital stock K_0 is greater than $\overline{K_0}$:*

$$K_0 > \overline{K_0} = \hat{K} - \frac{\frac{\partial V_2^F}{\partial K}|K = \hat{K}}{2r\gamma},$$

where $\hat{K} = \frac{3M-\alpha-2c^x}{3A}$ and V_2^F is the value function of the follower in the stage of joint production before the steady state.

The feedback clean investment strategy during entry deterrence is

$$I(K) = \frac{\frac{\partial V_2^F}{\partial K}|K = \hat{K}}{2\gamma} - r(\hat{K} - K). \tag{4}$$

The derivation of Proposition 3 is in Appendix A.4, and consists of finding values of K_0 which makes $I(K_0)$ as defined by (4) greater than 0. The first term of equation (4) is the marginal benefit of investment over the marginal cost of investment in the joint production stage, and the second term is the distance between the current capital level and the capital threshold for positive clean production. When $K = \hat{K}$, the clean investment is just the ratio of its marginal benefits to its marginal cost at that point. When $K < \hat{K}$, the second term is negative, making investment smaller. If K is sufficiently small or the discount rate r is sufficiently large, the second term may dominate the equation and make optimal investment non-positive. Hence, the initial capital stock K_0 needs to meet the condition in Proposition 3 for investment to occur prior to production.

Several key insights can be drawn from this condition. First, if the current capital level is far from the threshold required to produce, it may be optimal to stay out of the market. Second, if the discount rate r is high, the potential future profits are more heavily discounted, making the clean producer more likely to stay out of the market. Third, if the cost of investment γ is high, the potential future profits are less appealing because of the high cost, and the clean producer is less likely to invest. Finally, if the potential return to capital in the future $\frac{\partial V_2^F}{\partial K}|K = \hat{K}$ is high, the clean producer is likely to invest and enter the market.

Putting the results from the three phases together, we get a complete picture of the feedback strategies for both firms, as illustrated in Figure 1. The top panel shows the dirty and clean production rates as the functions of K. If the market price is higher than $C^y(K)$, that is $K < \frac{M-P_0}{A}$, the dirty producer does not consider the clean producer as a threat and maintains his monopoly price P_0. If $C^y(K) = P_0$, it is potentially profitable for the clean producer to enter the market, hence the dirty producer initiates entry deterrence by increasing the production to drive down the market price. When $K = \hat{K} = \frac{3M-\alpha-2c^x}{3A}$, entry deterrence ceases to be creditable and optimal and the dirty production rate linearly decreases in K until the capital stock reaches the steady state level $\frac{M-c^y}{A}$. On the other hand, clean production does not start until the entry deterrence stops at $\hat{K}$, then increases linearly in K until the steady state. In the steady state, if $5(c^x - c^y) > (\alpha - c^x)$, the clean sector has a higher production rate than the dirty sector and controls the majority of the market share.

Figure 1 also makes clear that the clean sector will not invest in knowledge capital unless the initial capital stock is greater than $\overline{K_0}$. If $K_0 > \overline{K_0}$, the clean sector starts to invest before production, and the investment rate linearly increases in K until it reaches $\hat{K}$. After that, clean production begins and the clean investment rate initially increases in K but gradually declines because the shadow value of K decreases as the system approaches the steady state. At $K = \frac{M-c^y}{A}$, the minimum clean

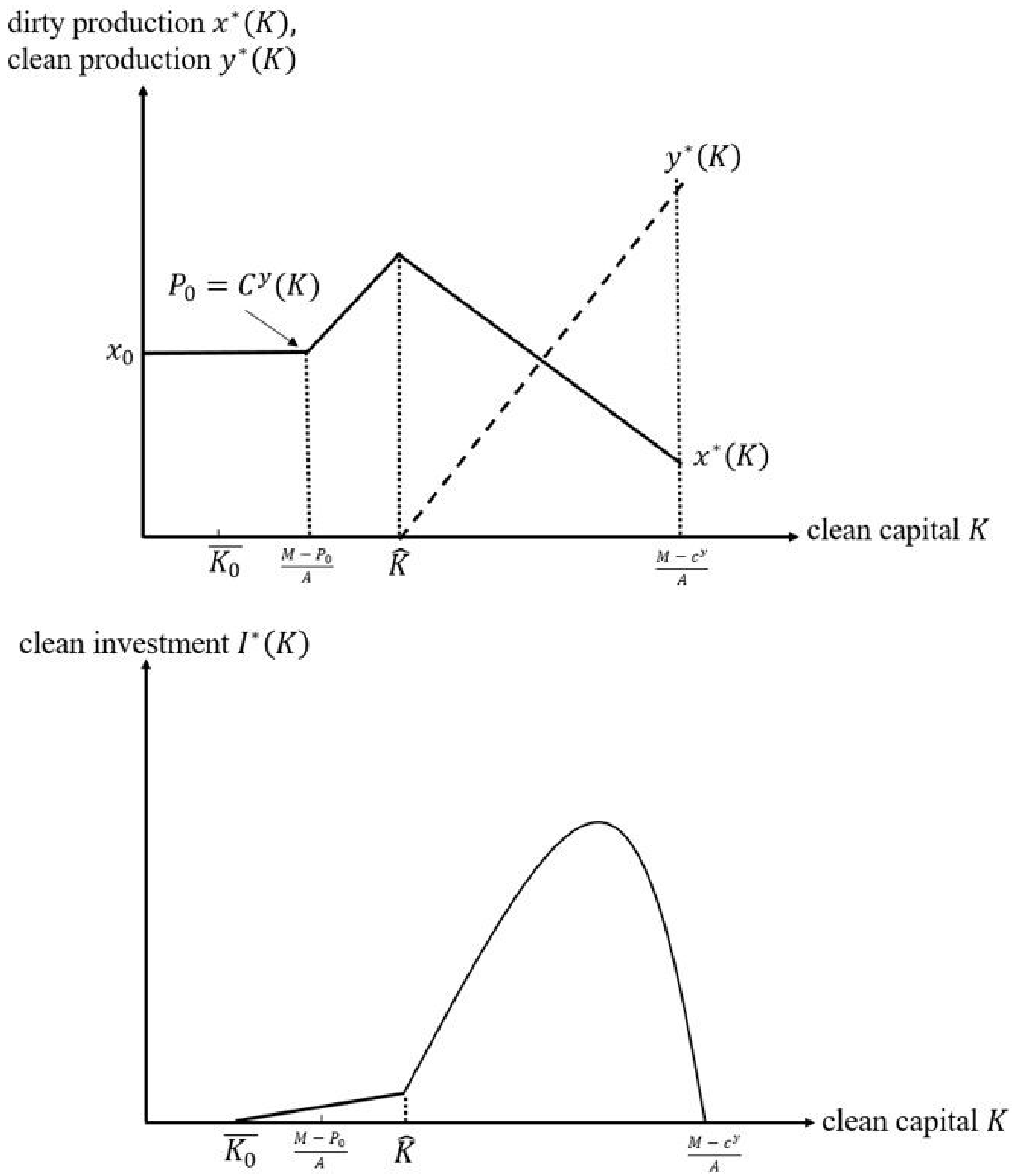


Figure 1: Stackelberg feedback strategies

production cost is reached and additional capital does not increase the value function. Hence, the optimal investment rate becomes zero and the transition reaches the steady state.

In summary, with the presence of the dirty producer's market power and non-exhaustible resources, the transition to clean technology can only be achieved if the initial capital condition in Proposition 3 is met, which is more likely with a low discount rate, a low clean investment cost, high marginal returns on clean capital, a sufficient initial capital stock, or combinations of these factors. If the clean producer needs to invest in capital before starting production, the dirty producer will initiate entry deterrence to keep out the clean producer until the clean production cost is sufficiently low.

4 Comparative Statics

Having solved for the equilibrium strategies, we next examine how the dirty producer's degree of market power influences the transition to cleaner technology. A useful starting point is to quantify market power by the dirty producer's ability to influence the market price. Bresnahan (1989) introduces several ways to identify market power using data, including (1) comparative statics in demand, particularly the slope of demand curve, and (2) comparative statics in cost. In this section, we use these two comparative statics to examine how different levels of market power affect the transition process. It has been well established that a lower demand elasticity leads to greater market power: consumers are less responsive to price changes, hence the producer has more room to manipulate the market price (Borenstein and Bushnell, 1999). In addition, a lower production cost increases the cost advantage of the incumbent dirty producer, making it harder for the clean producer to compete in the Stackelberg game. Therefore, we look at how an inelastic demand curve (i.e. a higher β) and a lower dirty production cost (i.e. a low c^x) affect the transition. Since the optimal strategies do not have closed-form solutions, we use numerical methods to demonstrate the impact of greater market power.

Figure 2 compares the feedback investment in clean capital for three configurations: baseline [$\beta = 0.1$, $c^x = 9$], inelastic demand [$\beta = 0.12$, $c^x = 9$], and low dirty production cost [$\beta = 0.1$, $c^x = 7.2$]. Compared to the baseline scenario, the inverse demand elasticity β increases by 20% in

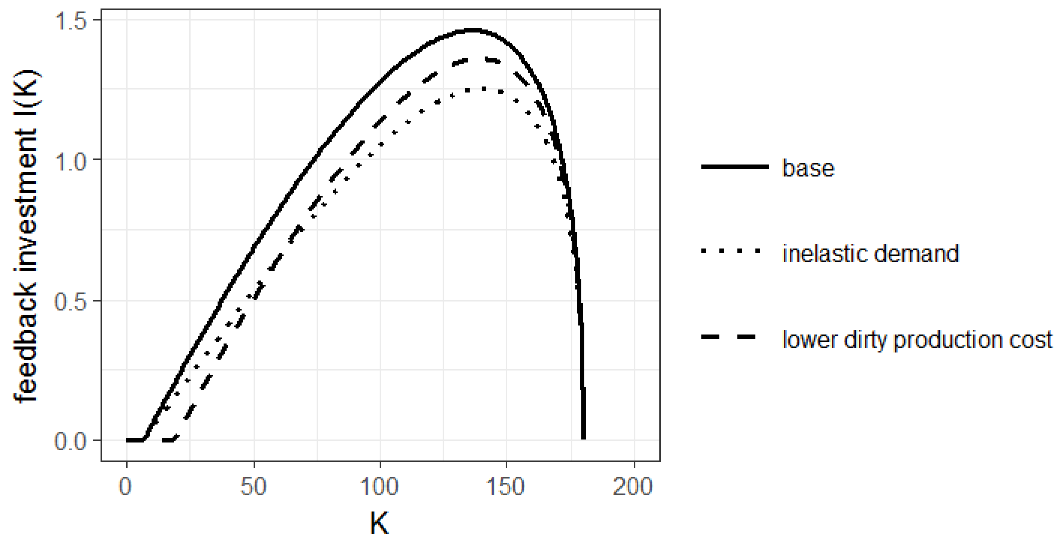


Figure 2: Optimal feedback strategies for clean capital investment

the second case, and the dirty production cost decreases by 20% in the third case.

If the market demand is inelastic ($\beta = 0.12$), the minimum capital requirement for the clean producer to invest and produce does not change much compared to the baseline level, but the feedback investment rate is lower. If the dirty producer produces at a lower cost ($c^x = 7.2$), the entry barrier for the clean producer is higher and the clean investment rate is also lower than the baseline. Overall, these results suggest that greater market power of the incumbent dirty producer increases the entry barrier for the clean producer and reduces the incentive for rapid investment in clean knowledge capital.

We also examine the effects of market power (via demand elasticity and dirty production costs) on the equilibrium paths of investment and production. The beginning capital levels are set equal and above the minimum capital requirement for clean production $\hat{K}$ in all three cases, hence there is no entry deterrence in this example. Figure 3 shows the equilibrium transition paths for the three configurations discussed above. Panel A shows the path of clean investment, which gradually increases for the most part of the transition before rapidly declining to zero. When the investment rate reaches zero, the transition process completes and the steady state is reached. When the dirty producer has greater market power because of either inelastic demand or lower production cost, the clean investment rate is lower than the baseline level and peaks at a later time compared to the baseline case. Panel B shows the growth path of clean capital as the result of investment. The capital

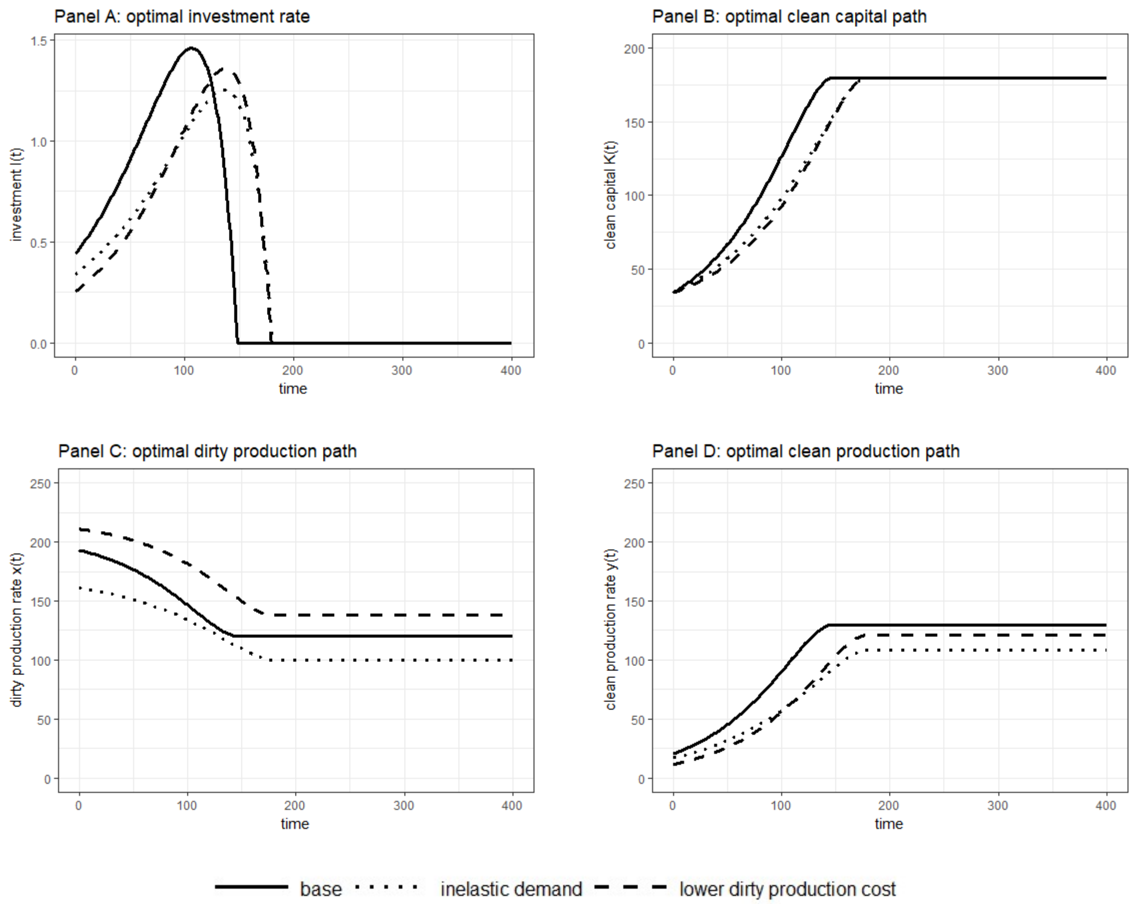


Figure 3: Optimal transition paths

stock at the steady state is the same in all three cases because it is defined by $C^y(K) = M - AK = c^y$. Since the investment rate is lower when the dirty producer has greater market power, it takes longer to reach the steady state. In this example, a 20% increase in the inverse market elasticity β and a 20% reduction in dirty production cost c^x extend the transition period by 20.82% and 21.62%, respectively. Panels C and D show the equilibrium path of the dirty and the clean production rate. The dirty producer is a monopoly before the clean producer plans to enter the market. As clean capital increases, the clean production cost declines, which reduces the cost advantage of the dirty producer. Hence, the dirty production rate decreases while the clean production rate increases during the transition. If the dirty production cost is low, the dirty production rate is higher and the clean production rate is lower than the baseline level because of the competitive cost advantage. If the market demand is inelastic, both the dirty and the clean production rates are lower than the baseline level (a 20% decline in elasticity leads to 16.67% drops in long run production rates by both producers). In contrast, in the case of a lower dirty production cost, the dirty producer could retain the majority of the market in the steady state. The numerical example indicates that a 20% decline in dirty production cost raises steady state dirty production up by 15% and reduce steady state clean production by 6.92%.

Overall, a lower dirty production cost equips the dirty producer with greater market power for entry deterrence. Once the clean producer is able to produce profitably, the dirty producer suppresses investment in clean capital through higher production levels. On the other hand, inelastic market demand does not exacerbate entry deterrence, but does suppress clean investment once it starts. When market demand is inelastic, both the dirty and the clean producer have incentive to withhold production and maintain a higher market price.

In the next section, we discuss the policy instruments that help reduce environmental damages from dirty production and avoid an environmental disaster.

5 Environmental policy implications

So far we have examined the transition process from dirty to clean production without the consideration of environmental damages from pollution or policy interventions that may help lower emissions. In this section, we first introduce a model of pollution, then study three potential interventions.

5.1 Environmental damages

To reflect concerns over damages and tipping points triggered by pollution, we adopt the approach in Acemoglu et al. (2012), which assumes that if a critical pollution threshold is reached, an "environmental disaster" occurs. Letting S_t denote the cumulative pollutant stock and $\overline{S}$ the critical threshold, disaster occurs if $S_t \geqslant \overline{S}$ at any time t. The pollutant stock increases with emissions and declines with decay as follows:

$$\dot{S}_t = \eta x_t - \delta S_t, \tag{5}$$

where η is the emission intensity of dirty production and δ is the rate of pollutant sequestration or decay. All other parts of the model presented earlier remain unchanged.

Before considering policy interventions, we note that without policy intervention, an environmental disaster can only be avoided under certain conditions:

PROPOSITION 4: *The long run equilibrium pollutant stock* S^* *is* $\eta x^*/\delta$. *Without policy intervention, an environmental disaster can be avoided if* $\eta x^*/\delta \leqslant \overline{S}$ *and* $\hat{S} < \overline{S}$, *where* $\hat{S}$ *is the peak pollutant stock level during the transition (if the transition occurs), and* x^* *is the equilibrium dirty production level.*

The proof of Proposition 4 is presented in Appendix A.5. By definition, the environmental disaster can be avoided only if both $\hat{S}$ and S^* lie below $\overline{S}$, and Proposition 4 provides the conditions under which $S^* < \overline{S}$. Intuitively, a disaster is more likely to be avoided when (1) the equilibrium dirty production level is low, (2) the emissions intensity of dirty production is low, and (3) the rate of pollutant sequestration is high.

The rest of this section analyzes the policy instruments that can help avoid an environmental disaster by influencing output of the clean and dirty producers and, as a result, emissions.[4]

5.2 Impact of policies on emissions and pollutant stock

In this section, we assess the effect of different policies on emissions and the resulting pollutant stock. Specifically, we compare three types of interventions: a constant tax τ for each unit of dirty production, a constant subsidy θ for each unit of clean production, and a proportional subsidy ρ for the cost of clean investment. The policies are assumed to take effect at time zero and remain in place forever.

To understand the impact of various policies, we first examine the long run pollutant stock $S^* = \eta x^*/\delta$. Clearly, reducing the equilibrium dirty production level x^* is an important channel for avoiding environmental disaster. Recall that the equilibrium dirty production level is (see section 2):

$$x^* = \frac{\alpha + c^y - 2c^x}{2\beta}. \tag{6}$$

A dirty production tax and a clean production subsidy can both reduce x^* through their effects on

[4] Emissions intensity and sequestration can, of course, also be affected by innovation and policies. Those considerations are beyond the scope of this paper, which allows us to focus on deterrence of clean producer entry and R&D by the incumbent.

c^x and c^y, respectively. From equation (6), we see that the marginal effect of an increase in the dirty tax on long run dirty production is twice as large (in magnitude) as the effect of a comparable increase in the clean production subsidy. Intuitively, the tax directly makes dirty production more expensive, while the subsidy reduces dirty production only indirectly as a result of lower marginal revenue due to increased clean production. While an analogous analytical expression is unavailable for the maximum pollutant stock level $\hat{S}$, numerical results indicate these general patterns continue to hold during the transition: both the dirty production tax and clean production subsidy reduce $\hat{S}$, with the former having a larger marginal effect than the latter. On the other hand, the R&D subsidy ρ for clean capital has no impact on the long run pollutant stock (ρ is absent from the expression for S^*) but can reduce $\hat{S}$ by encouraging clean investment and shortening the duration of the transition, thereby preventing the pollutant stock from exceeding the critical threshold.

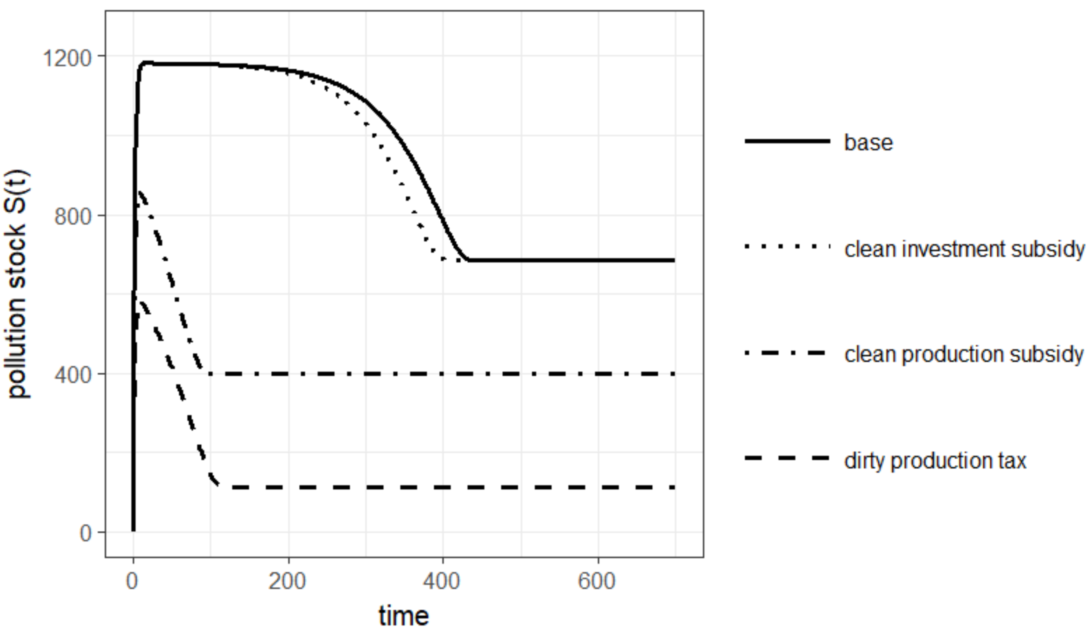


Figure 4: Pollution stock under different policies

To illustrate the effects of these policies on the pollution stock, Figure 4 depicts the paths of the pollution stock under these policies for a numerical example. In this example, we set $\tau = \theta$ and normalize $S_t = 0$ at $t = 0$. In all cases, S_t initially rises rapidly when the dirty producer dominates the market. After reaching its peak, S_t gradually declines as clean production ramps up, and the pollution stock eventually reaches the long run equilibrium level S^*. Both the dirty production tax and the clean production subsidy reduce (or eliminate) the duration of entry deterrence, prompting clean production to start earlier in the transition. For the same level of tax and subsidy, the tax results in lower S_t during the transition, consistent with the analysis of marginal effects above. In addition, S^* is lower under the dirty production tax as compared to that under the clean production subsidy. Finally, the clean investment subsidy reduces the cost of investment and accelerates the transition process, hence reducing emissions and the pollutant stock during the transition period. However, that effect is modest at the investment subsidy level used and, as noted above, the investment subsidy has no effect on the long run equilibrium pollutant stock.

Before turning our attention to a welfare comparison of the policies, we also examine how market power influences the impact of each policy on pollution levels $\hat{S}$ and S^*. As discussed in section 4, the incumbent producer has higher market power when its production cost is low (c^x is small) or market demand is inelastic (β is large). First, consider the impacts of the production tax and production subsidy on S^* (recall the investment subsidy has no effect on S^*, so we do not analyze it here). The tax τ affects S^* through c^x with $\frac{\partial S^*}{\partial \tau} = \frac{\partial S^*}{\partial c^x} = -\frac{1}{\beta}$, while the production subsidy θ has marginal effect $\frac{\partial S^*}{\partial \theta} = -\frac{\partial S^*}{\partial c^y} = -\frac{1}{2\beta}$. It is clear from these expressions that greater market power due to inelastic demand will reduce the marginal effects of either policy on the long run emissions level. In contrast, greater market power due to lower dirty production costs has no influence on the marginal effect of either policy on the long run pollution stock. Further, numerical results show that these insights carry over to the peak pollution stock $\hat{S}$: greater market power due to more inelastic demand (lower dirty production cost) reduces (has no effect on) the effect of either production policy on pollution.

In summary, a dirty production tax, a clean production subsidy, and a clean investment subsidy all reduce emissions and pollution levels during the transition period, and the first two also reduce the long run equilibrium pollution stock level. [5] With the effects of these policies on pollution established, we next examine the welfare consequences of each.

[5] Importantly, to have such an effect on the long run pollution stock, the dirty production tax and clean production subsidy need to be maintained forever. As stated earlier we also assume the investment subsidy is maintained forever, but since investment cannot reduce clean production costs below the lower bound, the investment subsidy could be removed once the lower bound is reached without an effect on the equilibrium.

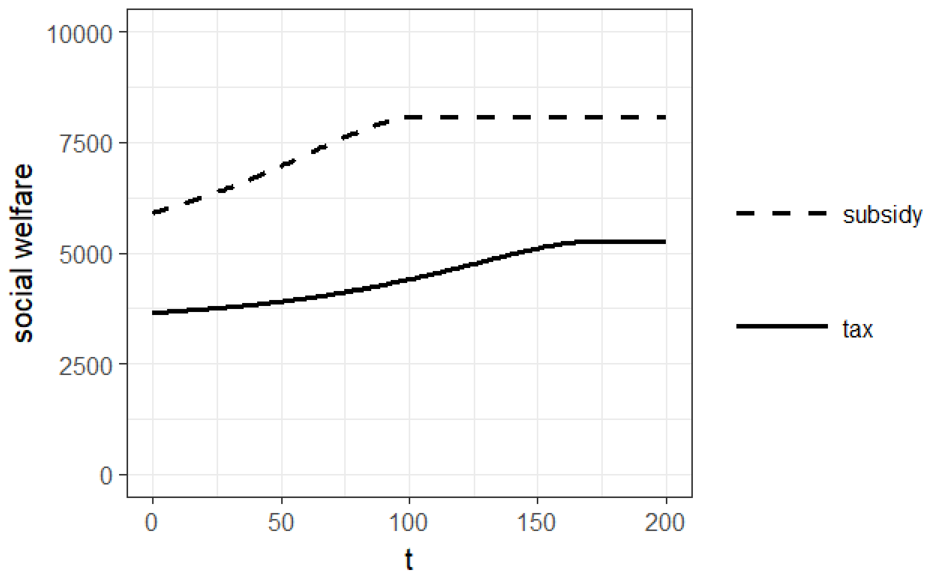


Figure 5: Social welfare path comparison

5.3 Social welfare comparison

To evaluate the candidate policies discussed above, we compare the social welfare consequences of the dirty production tax and clean production subsidy.[6] In this context, we define social welfare as the discounted sum of producer and consumer surplus, net of any subsidy payments or tax revenues. The environmental disaster framework we adopt influences welfare only by imposing a constraint on S_t. As a result, the best policy instrument conditional upon a pollution threshold $\overline{S}$ is that which generates the highest social welfare while ensuring $S_t \leq \bar{S}$ for all t. Since we define $\hat{S}$ as the peak pollution stock, this constraint is identical to $\hat{S} \leq \bar{S}$.

We first consider the use of a single policy: either the dirty production tax or a clean production subsidy. We solve numerically for the level of each instrument that produces $\hat{S} = \bar{S}$ and analyze the resulting equilibria. As an example, Figure 5 compares the time paths of welfare flows when the tax and subsidy are set such that $\hat{S} = \bar{S} = 991$. For this example, the clean production subsidy generates higher social welfare flows than the dirty production tax at all points in time, such that the discounted welfare under the production subsidy is higher than that for the tax. In fact, we find this to be true for all numerical simulations for any choice of pollution threshold $\bar{S}$. The intuition behind this

[6] Numerical simulations show that although an investment subsidy can reduce the peak pollution level, the effect is small compared to the impact of production-centric policies. This relationship holds for all feasible investment subsidies under a range of model parameters. Hence, we only focus our social welfare analysis on the production tax and subsidy.

finding is straightforward: in the absence of a policy and ignoring emissions consequences, market power leads both producers to choose outputs that are too low. Then, if the pollution threshold demands that dirty production be lowered, a subsidy can simultaneously reduce dirty production while incentivizing clean production, thereby addressing both market failures at once and improving welfare. In contrast, while the dirty production tax helps avoid the critical pollution threshold, it also encourages less production, which only exacerbates welfare losses from underproduction due to market power.

Figure 6 shows the relationship between discounted social welfare and the peak pollution stock when either a dirty tax or a clean subsidy is imposed. In the absence of any policy, the pollution stock and welfare are at the hollow point identified in the figure. As the tax increases, both peak pollution and welfare (conditional upon avoiding the environmental disaster) initially decline. Once the tax is large enough, the dirty producer initiates entry deterrence by producing more, which actually causes peak pollution to jump to a higher level. Further increases in the tax shift production toward the clean sector, which reduces peak pollution but causes declines in welfare due to further reductions in overall production. In contrast, the clean production subsidy has no effect for small levels because the clean producer does not enter the market. Once the subsidy becomes sufficiently large, the clean producer enters and the dirty producer increases production in response, causing peak pollution to increase. Further increases in the subsidy shift production toward the clean producer, causing a drop in peak pollution but also an increase in welfare since overall production levels (and consumer and producer surplus) increase. Note that for any fixed peak pollution level, welfare under the clean production subsidy is always higher than that under the dirty production tax.

We also consider the potential for the production tax and subsidy to be used jointly. However, per the logic outlined above, the tax imposes a welfare tradeoff by avoiding the environmental disaster but also exacerbating welfare losses due to underproduction. Our numerical simulations confirm this intuition, indicating that a corner solution involving only the clean production subsidy produces higher welfare for any pollution threshold $\bar{S}$.

Together, these results show that although the dirty production tax has a larger marginal effect on reducing emissions, it also lowers overall production in the market and hence social welfare given the presence of market power. A clean production subsidy, on the other hand, generates higher social welfare by reducing production cost in the market. Without considering any budget

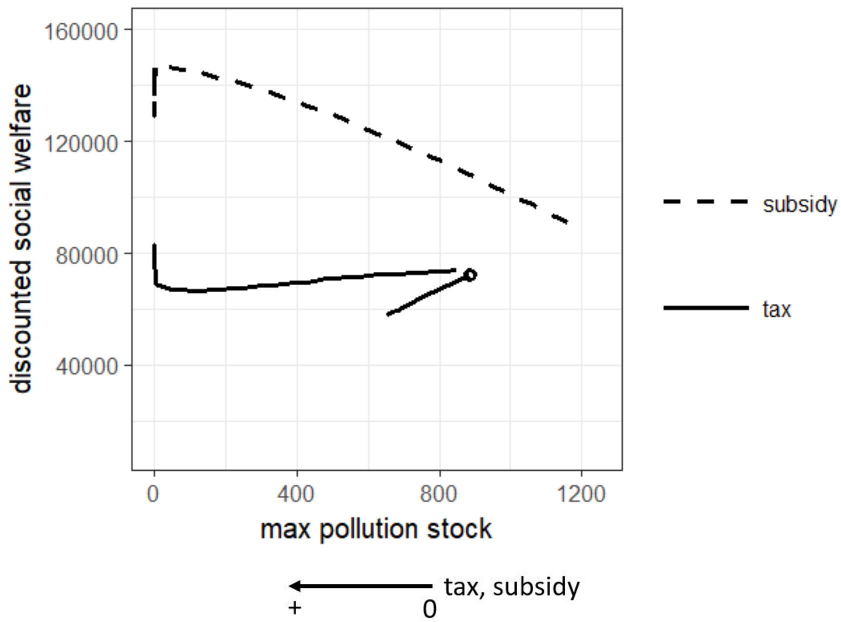


Figure 6: Discounted social welfare and peak pollution level

constraints faced by the regulator, the socially optimal policy portfolio consists only of a clean production subsidy to meet the pollution target. These results continue to hold even when the clean subsidy is large enough that the real cost of clean production is negative.

6 Conclusion

In this paper, we analyze the transition from dirty to clean technology and the effects of market power on the transition process using a dynamic Stackelberg game. We derive optimal feedback strategies that constitute a subgame-perfect equilibrium, illustrating how the incumbent polluting sector may deter entry by the emerging clean sector by increasing production. A high level of incumbent market power, characterized by low production cost or inelastic demand, raises the entry barrier for the clean sector and lowers investment in clean technology during the transition. Policy interventions, such as a dirty production tax, clean production subsidy, and clean investment subsidy, can reduce peak and long run pollution levels, though the investment subsidy has limited effect on peak pollution only. Although the dirty production tax has a stronger marginal effect on peak and long-run pollution levels, it leads to lower discounted social welfare than the clean production subsidy due to the already inefficiently low production levels that result from market power. Further, we find that in some cases it is optimal for the social planner to subsidize clean production beyond levels required to keep pollution levels below a critical threshold; further increases in the subsidy may continue to address underproduction.

Our analysis suggests several interesting directions for future work. First, both the dirty and clean production sectors are analyzed as single players in this paper. This simplification allows us to study the interactions between the two sectors without considering within-sector interactions among firms. It may also be instructive to model a market with a dominant polluting firm and a competitive clean fringe. In such a setup, R&D spillovers may create additional barriers to entry. Alternately, if there are multiple incumbent dirty producers, they may be able to collude and deter the entry of the clean industry, but such collusion could also break down. Second, our analysis assumes constant marginal cost in both the dirty and clean sectors, conditional upon current levels of knowledge capital in the clean sector. These assumptions facilitate derivation of the Stackelberg feedback strategies, but it would be interesting to examine the robustness of results to alternate cost functions. Similarly, while we employ an R&D model of technological change, clean production costs could also decline with cumulative production ("learning by doing"). If learning by doing occurs in the clean sector, then we would expect an accelerated transition process, though an incumbent dirty producer with knowledge of this should respond strategically by increasing its own production to inhibit learning. Finally, for tractability we have assumed the dirty producer always acts as a Stackelberg leader. Regime change could be incorporated in the analysis, allowing Cournot competition after the clean producer passes a market share threshold.

Chapter 2. Heterogeneous Direct Rebound Effect: Theory and Evidence from the Energy Star Program

Published as "Sun, B. (2018). Heterogeneous direct rebound effect: Theory and evidence from the Energy Star program. Energy Economics, 69, 335-349. https://doi.org/10.1016/j.eneco.2017.11.025"

Abstract

Improvements in energy efficiency change the relative prices of energy services and thus the consumption of those services. This so-called direct rebound effect changes the energy savings that improved efficiency might otherwise achieve. This paper develops a theoretical model that shows the sign of the direct rebound effect depends on the type of energy service. Empirical evidence from the 2009 Residential Energy Consumption Survey data shows a negative direct rebound effect for Energy Star dishwashers and a potentially positive direct rebound effect for Energy Star air conditioners. Negative rebound effects amplify energy savings, while positive rebound effects offset energy savings from using more efficient technologies.

Keywords: Direct rebound effect Energy, Energy efficiency, Energy Star

1 Introduction

Energy conservation through improved efficiency is likely to play an important role in mitigating climate change. In 2012, the residential sector accounted for 21% of total primary energy consumption and 20% of total carbon emissions in the U.S. (U.S. Environmental Protection Agency, 2015). By adopting energy efficiency measures, households can not only lower their utility bills, but also help mitigate local pollution problems and greenhouse gas emissions. As energy efficiency measures reduce the amount of energy consumed for certain household tasks (e.g., a load of laundry), those tasks become relatively cheaper. Consequently, consumers might change how much they use these energy services (e.g., doing more loads of laundry), which affects total energy savings and emission reduction. The change in energy savings due to this behavioral response is often defined as a “direct rebound effect”.

The Energy Star program was first introduced by the U.S. Environmental Protection Agency (EPA) in 1992, and has evolved to cover over 70 different product categories in 2013 (EPA, 2015). In order for a product to become Energy Star certified, it must meet a set of energy efficiency standards. For instance, Energy Star certified dishwashers should be 12% more efficient than non-certified models, and Energy Star certified room air conditioners should be 10% more efficient than non-certified models[7]. There has been some empirical evidence showing that Energy Star certified buildings are effective at reducing energy consumption (Jones et al., 2010; Li and Carrión-Flores, 2017), but little is known about the effectiveness of Energy Star appliances on savings. According to the 2013 annual report published by the EPA, Energy Star products and certified homes generated 21.6 billion dollars of economic benefits and avoided 158.2 million metric tons of greenhouse gas emissions in 2013. However, the EPA’s calculations on annual energy savings are based on the difference in annual energy use between a single Energy Star product and a non-certified product, assuming that households do not change their energy consuming behavior in response to improved efficiency. Hence, it is possible that the EPA provides inaccurate estimates of the Energy Star’s program impact on energy conservation and greenhouse gas reduction. Quantifying the rebound effect in the Energy Star program can offer additional insight on the program’s impact and the design of energy efficiency policies.

This paper develops a theoretical model in which a household chooses the efficiency level of an energy service and how to use it. The model shows the sign of the direct rebound effect depends the marginal utility of the energy service. The empirical analysis quantifies the direct rebound effect for Energy Star dishwashers and room air conditioners using the 2009 Residential Energy Consumption Survey (RECS). Because households who purchased Energy Star appliances are likely to be different from those who did not (i.e., sample selection bias), this paper uses the regional adoption rate of Energy Star appliances as an instrument. Estimation results suggest a negative direct rebound effect for Energy Star dishwashers and a potentially positive direct rebound effect for Energy Star room air conditioners. This means higher energy efficiency potentially leads to lower frequency of using dishwashers and higher frequency of using air conditioners. In addition, having an Energy Star dishwasher contributes to lower electricity consumption, while having an

[7]For more information on Energy Star certification standards, see https://www.energystar.gov/.

Energy Star room air conditioner leads to no change or an increase in electricity consumption. These findings suggest that a negative direct rebound effect is likely to amplify the energy savings while a positive direct rebound effect is likely to offset the energy savings.

Economists have long argued that efficiency gains can lead to increased consumption (Jevons, 1906; Domar, 1962; Alcott, 2005). In more recent literature, mostly in the context of energy efficiency programs, the rebound effect is defined as the difference between the achieved reductions in energy use and the predicted reductions in energy use when consumer and market response is ignored (Gillingham et al., 2016). Empirical evidence of the rebound effect has been well documented for various technologies, scope, regions and time period of analysis (Greening et al., 2000; Sorrell et al., 2009; Azevedo, 2014; Gillingham et al., 2016). Theoretically, the direct rebound effect is the elasticity of demand for an energy service with respect to its energy efficiency (Sorrell et al., 2009). This effect is traditionally approximated by the elasticity of energy demand with respect to energy price (Sorrell et al., 2009; Azevedo, 2014; Gillingham et al., 2016). This approach was first introduced by Khazzoom (1980) who showed that the elasticity of energy demand with respect to appliance efficiency is equivalent to the elasticity of energy demand with respect to energy prices under certain assumptions. It implicitly equates the direct rebound effect to a behavioral response to the lower cost of energy services (Sorrell et al., 2009). Due to the limited data on demand for energy services and their efficiency, energy price elasticity became a popular proxy for measuring the rebound effect (Schwarz and Taylor, 1995; Gillingham, 2012; Greene, 2012). However, these assumptions are fairly strong and often unrealistic, including (1) there is only one energy service; (2) the only marginal cost of the energy service is the energy price; (3) the energy efficiency investment is reversible (Binswanger, 2001). In addition, consumers may not be responsive to the changes in electricity price. Some early studies found electricity demand to be price-inelastic in the short-run (Azevedo, 2014). Lee at al. (2010)examined the elasticity of electricity demand in 25 OECD countries between 1978 and 2004, and concluded that the long-run price electricity demand is inelastic(-0.01). Moreover, electricity is usually subject to increasing-block pricing instead of linear pricing schedule, which means consumers may not know the marginal price of electricity during a billing period (Borenstein, 2009). Hence, approximating rebound effects in electrical appliances using energy price elasticity might lead to biased estimates. The elasticity of an energy service with respect to its cost can approximate the direct rebound effect if a measure of the energy services is available. Most of these studies focus on the personal automobile sector (Greene, 2012; Schimek, 1996; Small and Van Dender, 2007) and the spacing heating sector (Guertin et al., 2003). In addition, Gillingham et al. (2016) pointed out that ”no causality, no rebound”, since there are many factors influencing energy demand. Hence, it is important to establish the causal relationship between improved efficiency and the demand for the energy services when studying rebound effects.

The contribution of this paper is threefold. First, I develop a theoretical framework in which each household can make an irreversible investment in efficiency, and show that the sign of the direct rebound effect depends the marginal utility of the energy service. I then test this claim by comparing the direct rebound effects for Energy Star dishwashers and room air conditioners, and show that the type of appliance determines the sign of the direct rebound effect. Prior work usually focuses on a single energy service and does not consider whether the rebound effect differs across energy services. Second, instead of using price elasticity as a proxy, I estimate the direct rebound effect as the impact of higher efficiency on the frequency of appliance use. Finally, this paper contributes to the lack of empirical evidence on the direct rebound effect in the residential appliance sector.

The rest of the paper is organized as follows. Section 2 develops a two-period household choice model which generates hypotheses on the signs of the direct rebound effects for Energy Star dishwashers and room air conditioners. Section 3 describes the data used in the empirical analysis. Section 4 presents the empirical framework. Section 5 presents the estimation results and Section 6 concludes with policy implications.

2 Theoretical Framework

2.1 Modeling direct rebound effect

This section introduces a two period household choice model that characterizes the impact of energy efficiency on the frequency of appliance use. Let s be the level of appliance service demanded by the household (e.g., the frequency of using a dishwasher), y be the composite good representing the income spent on other goods and services, and x be a vector of household and environmental characteristics. The household's utility function depends on these three variables $u(s, y; x)$. The utility function is assumed to be strictly increasing and concave in both s and y (i.e., diminishing return to the consumption of goods and services): $u_s > 0, u_{ss} < 0$; $u_y > 0, u_{yy} < 0$. Subscripts are used to denote partial derivatives. No assumption is imposed on u_{sy} as I later show that the sign of the direct rebound effect depends on the sign of u_{sy}.

In addition to choosing the level of appliance service s, the household also decides on the energy efficiency of the appliance, denoted by η. The total amount of energy devoted to providing the appliance service is $E = s/\eta$: a more efficient appliance uses less energy for a given level of service. The cost of improving efficiency of the appliance is $c(\eta)$, which is an increasing function of η (i.e., $c_\eta > 0$). Here, s and η are considered to be continuous variables to simplify the analysis. Let p denote the energy price associated with E, w denote the exogenous income level in both periods, and δ denote the time discount factor.

In the first period, the household does not have the appliance (i.e., $s = 0$) and chooses the level of energy efficiency (η) of the appliance to invest in.[8] In the second period, the household decides on the optimal demand for appliance service (s) given the level of η chosen in the first period. Thus, the household's utility maximization problem is

$$\max_{s,\eta} u(0, y_1; x) + \delta u(s, y_2; x),$$

where $y_1 = (w - c(\eta))$ and $y_2 = (w - ps/\eta)$. The direct rebound effect is defined as $\partial s(\eta)/\partial\eta$. Assuming perfect information and interior solution, I first solve for the optimal level of s given η (i.e., $s(\eta)$), then the optimal level of η. The optimal $s(\eta)$ equates the marginal utility of appliance service with the marginal utility of spending on other goods as the result of energy savings in the second period (equation 7).

$$u_s(s, y_2, x) = \frac{p}{\eta} u_y(s, y_2, x). \tag{7}$$

The optimal η is derived by considering the cost of investing in energy efficiency η in the first period and the indirect impact on utility through $s(\eta)$ in the second period. The condition for the optimal η is:

$$u_y(y_1; x) c_\eta = \delta u_s(s, y_2; x) \frac{\partial s(\eta)}{\partial\eta} - \delta p u_y(s, y_2; x) \left[\frac{1}{\eta} \frac{\partial s(\eta)}{\partial\eta} - \frac{s(\eta)}{\eta^2} \right]. \tag{8}$$

[8] Another way to consider this is that the service demand is normalized to zero in the first period, and s in the second period is change in demand for service.

2.2 Sign of direct rebound effect

This section discusses the sign of the direct rebound effect, which depends on u_{sy} and the elasticity of marginal utility with respect to s. The sign can be positive or negative with sufficient conditions for each case given in Proposition I:

Proposition I. *Define ξ_{u_s} as the elasticity of marginal utility with respect to s:*

$$\xi_{u_s} = \left| \frac{\partial u_s(s,y_2;x)}{\partial s(\eta;x)} \frac{s(\eta;x)}{u_s(s,y_2;x)} \right| .$$

Suppose the marginal utility of appliance service is non-increasing in income (i.e., $u_{sy} \leqslant 0$). Then the rebound effect is positive for $\xi_{u_s} < 1$ and negative for $\xi_{u_s} > 1$.

Proof. The direct rebound effect can be written: [9]

$$\frac{\partial s(\eta)}{\partial \eta} = \frac{\overbrace{c_\eta u_y(y_1,x)}^{(+)} - \overbrace{\eta c_\eta^2 u_{yy}(y_1,x)}^{(-)} - \overbrace{\delta p s^2 u_{sy}(s,y_2,x)/\eta^2}^{(-)}}{\delta s\left(u_{ss}(s,y_2,x) - p u_{sy}(s,y_2,x)/\eta\right) + \delta u_s(s,y_2,x)}. \tag{9}$$

The assumptions on the utility and cost functions suggest that $u_y > 0$, $u_{yy} < 0$ and $c_\eta > 0$. If the marginal utility of the appliance service is non-increasing in income (i.e., $u_{sy} \leqslant 0$), the numerator of equation (9) is positive. The sign of the direct rebound effect thus depends on the sign of the denominator. An positive rebound effect requires

$$\delta s\left(u_{ss}(s,y_2,x) - p u_{sy}(s,y_2,x)/\eta\right) + \delta u_s(y_2,x) > 0. \tag{10}$$

Since $y_2 = w - ps/\eta$, equation (10) implies the elasticity of marginal utility with respect to s must satisfy the following condition for a positive direct rebound effect:

$$\partial s(\eta)/\partial \eta > 0 \Rightarrow \quad \xi_{u_s} = \left| \frac{\partial u_s(s,y_2;x)}{\partial s(\eta;x)} \frac{s(\eta;x)}{u_s(s,y_2;x)} \right| < 1. \tag{11}$$

If there is a negative direct rebound effect of the appliance, then $s u_{ss}(y_2,x) + u_s(y_2,x) < 0$ must hold, which implies the elasticity of marginal utility with respect to s (ξ_{u_s}) must satisfy

[9] For derivation, see B.1.

$$\partial s(\eta)/\partial \eta < 0 \Rightarrow \quad \xi_{u_s} = \mid \frac{\partial u_s(s, y_2; x)}{\partial s(\eta; x)} \frac{s(\eta; x)}{u_s(s, y_2; x)} \mid > 1. \tag{12}$$

■

The intuition of Proposition I is that if the marginal utility of the appliance service reduces slowly as the service level goes up, then higher appliance efficiency induces higher service demand, offsetting the energy savings from the improved efficiency. One the other hand, if the marginal utility of the appliance service reduces rapidly as the service level goes up, then there would be a negative rebound effect, which enhances the energy saving from improved efficiency. When the marginal utility of the appliance service increases with income (i.e., $u_{sy} > 0$), the sign of the direct rebound effect cannot be determined by ξ_{u_s}. When $\xi_{u_s} = 1$, $u_{sy} < 0$ leads to a positive direct rebound effect while $u_{sy} > 0$ leads to a negative direct rebound effect, assuming the third order derivatives of the utility and cost functions are zero.[10]

A summary of the sign of the direct rebound effect under different conditions is presented in Table 1.

Table 1: Sign of the direct rebound Effect $\partial s(\eta)/\partial \eta$

	$u_{sy} < 0$	$u_{sy} = 0$	$u_{sy} > 0$
$\xi_{u_s} < 1$	+	+	+/-/0
$\xi_{u_s} > 1$	-	-	+/-/0
$\xi_{u_s} = 1$	+	+/-/0	-

For appliances that only meet basic living needs, $u_{sy} \leqslant 0$ is likely to hold because as the household has higher income (or high consumption of other goods), the appliance service brings equal or lower marginal utility to the household. Moreover, for appliance services that require additional labor input, such as doing dishes, the marginal utility of using a dishwasher is likely to decline rapidly as the frequency of doing dishes increases (i.e., $\xi_{u_s} > 1$). On the other hand, using an air conditioner requires little effort, so the marginal utility is likely to decline slowly as service frequency goes up (i.e., $\xi_{u_s} < 1$). Therefore, I expect to see a negative direct rebound effect for Energy Star dishwashers and a positive direct rebound effect for Energy Star room air conditioners.

The analytical results from this model contrast with previous work on the direct rebound effect. As mentioned in the introduction, the direct rebound effect is usually approximated by the elasticity

[10] For derivation, see B.1.

of demand with respect to energy price, and the role of appliance service in the household utility function is often overlooked. These results address the importance of the relationship between the appliance service and the household's marginal utility in the discussion of the direct rebound effect.

3 Data and Descriptive Statistics

The primary data set in this paper is the 2009 Residential Energy Consumption Survey (RECS) micro data. The U.S. Energy Information Administration (EIA) has conducted RECS once every four years since 1978. The survey collects residential energy usage data for housing units in a nationally representative sample. In addition to the energy-related data, the EIA also collects data on the characteristics of the sampled housing units and household demographics. In order to capture the most complete and accurate information on household energy consumption and expenditure, the EIA conducts follow-up surveys with energy suppliers after the household survey.

The universe for the 2009 RECS sample design includes all housing units that are occupied as primary residences in all 50 States and the District of Columbia. It excludes secondary homes, vacant units, military barracks and common area in apartment buildings. The 2009 survey collects data from 12,083 households that are statistically selected to represent 113.6 million housing units, which are equivalent to 64 percent of the U.S. population and 63 percent of all homes occupied as primary residences[11].

To study the rebound effect in using Energy Star dishwashers, I restrict the sample to the households that had dishwashers at the time of the survey and had purchased them between 2005 and 2009 (i.e., the dishwashers are less than 5 years old at the time of the survey). Hence, all the households in the sample had fairly recently made a decision on what type of dishwasher to purchase. When the respondents were asked "whether your dishwasher is an Energy Star appliance", they were presented with an Energy Star label card. About 6.5% of the respondents in the previously specified group could not give a yes-or-no answer. Murray and Mills (2011) use the 2005 RECS data to show that the respondents who were aware of the Energy Star label are systematically different from those who were not, and the unobserved heterogeneity between these groups might significantly bias the estimates in the purchase decision model. In addition, households who do not pay their

[11] For more information on RECS survey and data collection procedures, see the EIA website: `http://www.eia.gov/consumption/residential/data/2009/`.

Table 2: Descriptive statistics of the Energy Star dishwasher sample, N = 1761

Variable	Mean	Std.Dev
Dependent Variables		
Frequency of using dishwasher*	3.419	1.207
Annual electricity consumption for small appliances** (kilowatt-hours)	8260.69	4806.42
Energy and Appliance Usage		
Dishwasher is Energy Star (=1)	0.867	0.340
Dishwasher less than 2 years old in 2010 (=1)	0.433	0.496
Have microwave oven (=1)	0.986	0.116
Number of stoves	0.873	0.392
Number of separate ovens	0.248	0.555
Frequency of cooking hot meals (0:never cooks, 6:three or more times a day)	4.022	1.040
Have Energy Star clothes washer (=1)	0.559	0.497
Have Energy Star refrigerator (=1)	0.609	0.488
Average electricity price in 2009 ($/kWh)	0.127	0.059
Had home energy audit before (=1)	0.074	0.262
Housing Characteristics		
House in urban area (=1)	0.777	0.416
Age of house in 2010	36.02	23.43
Number of years living in the house in 2010	2.508	1.445
Own the house (=1)	0.903	0.295
Rent the house (=1)	0.090	0.286
Occupy without payment (=1)	0.007	0.082
Total square footage of the house	2886.71	1575.36
Household Demographics		
Householder lives with spouse or partner (=1)	0.765	0.424
2009 gross household income (1:less than $2500, 24:$120,000 or more)	16.766	6.397
Number of household members	2.872	1.394
Education level (0:no schooling, 8:Doctorate degree)	3.966	1.624

* Frequency scale of using dishwasher: 1 - less than once a week, 2 - once each week.
3 - 2 or 3 times a week; 4- 4 to 6 times a week, 5 - at least once a day.
** Annual electricity consumption excludes spacing heating, space cooling, water heating and refigeration

own electricity bills are likely to have different energy using behavior. Therefore, the sample also excludes households that were not aware of Energy Star labels or did not pay their own electricity bills at the time of the survey. The same criteria are also applied to the households that had room air conditioners at the time of the survey.

Table 2 shows the descriptive statistics of the dishwasher sample, which has 1,761 observations. There are five levels of dishwasher use frequency, with "1" representing less than once a week and "5" representing at least once a day. The average frequency is between level 3 and 4, which represents "two or three times a week" and "four to six times a week", respectively. The annual electricity consumption excluding space heating and cooling, water heating and refrigeration is 8,260 kilowatt-hours. About 86.7% of the households in the sample have Energy Star dishwashers and less than half of them are less than two years old at the time of the survey. The average electricity price in 2009 is calculated as the total electricity cost in dollars divided by the total electricity usage in kilowatt-hours from the energy supplier survey. I include the variables on housing characteristics and household demographics that are likely to influence the decision to purchase Energy Star appliances and the frequency of use.

Table 3: Descriptive statistics of the Energy Star room air conditioner sample, N = 907

Variable	Mean	Std.Dev
Dependent Variables		
Frequency of using the most used room air conditioner*	1.699	0.838
Annual electricity consumption for space cooling (kilowatt-hours)	1032.03	1482.05
Energy and Appliance Usage		
Most used room air conditioner is Energy Star (=1)	0.800	0.399
Most used room air conditioner less than 2 years old in 2010 (=1)	0.364	0.481
Have central air conditioner (=1)	0.061	0.239
Number of room air conditioners	1.92	1.018
Number of ceiling fans used	1.741	1.78
Have Energy Star clothes washer (=1)	0.361	0.481
Have Energy Star refrigerator (=1)	0.438	0.496
Dehumidifier used (=1)	0.153	0.360
Average electricity price in 2009 ($/kWh)	0.043	0.023
Had home energy audit before (=1)	0.0507	0.22
Housing Characteristics		
House in urban area (=1)	0.799	0.401
Age of house in 2010	53.4	23.9
House shaded from sun by large trees (=1)	0.456	0.498
Number of years living in the house in 2010	2.53	1.62
Own the house (=1)	0.608	0.489
Rent the house (=1)	0.029	0.481
Occupy without payment (=1)	0.007	0.167
Total square footage of the house	1800	1187
Total number of rooms in the house	5.54	1.93
Household Demographics		
Household members received employment income in 2009 (=1)	0.785	0.411
Householder lives with spouse or partner (=1)	0.601	0.49
2009 gross household income (1:less than $2500, 24: $120,000 or more)	12.1	6.78
Number of household members	2.83	1.62
Education level (0:no schooling, 8:Doctorate degree)	2.98	1.67
Climate Characteristics		
Cooling degree days in 2009, base temperature 65F	1184	996
Cooling degree days, 30-year average 1981-2010, base 65F	1248	913

* Frequency scale of using room air conditioner: 1 - Turned on only a few days or nights when really needed, 2 - Turned on quite a bit, 3 - Turned on just about all summer

Table 3 shows the descriptive statistics of the room air conditioner sample which has 907 observations. For households that have multiple air conditioning units, the characteristics of the most used unit are reported. There are three levels of room air conditioner use, with "1" representing "turned on only a few days or nights when really needed, 2 representing "turned on quite a bit" and 3 representing "turned on just about all summer". On average, the households in the sample consume 1032 kilowatt-hours of electricity for space cooling and about 80% of them have an Energy

Star room air conditioner. In addition to the appliance, housing and demographic characteristics, I also include climate characteristics: cooling degree days in 2009 and 30 year average. Cooling degree days is a measure of how hot a location is over a period of time. It is calculated as the difference between a day's average temperature and the base temperature (65F in this survey), and the daily temperature difference is summed over all the days with average temperature above 65F.

The RECS data do not contain any information on the price paid for the appliances or the capacity of the appliances. Hence, the only indicator of appliance efficiency is whether the appliances are Energy Star certified or not. The Energy Star website managed by the EPA provides detailed capacity information on the appliances available on the market after 2011, but not during the period when the 2009 RECS respondents purchased their appliances.

Table 4: Region level characteristics

State(s)	Incentive 2008	ACEEE 2008	Incentive 2009	ACEEE 2009	AWE 2011
CT,ME,NH,RI,VT	0.27	0.50	0.53	0.59	12.00
MA	0.33	0.53	0.67	0.78	13.00
NY	0.33	0.65	0.67	0.69	11.00
NJ	0.00	0.51	0.00	0.46	16.50
PA	0.67	0.34	1.00	0.44	3.00
IL	0.67	0.32	0.67	0.32	5.00
IN,OH	0.17	0.22	0.42	0.28	4.75
MI	0.00	0.12	0.33	0.20	3.00
WI	0.00	0.52	0.33	0.48	15.50
IA,MN,ND,SD	0.22	0.32	0.25	0.31	7.75
KS,NE	0.33	0.12	0.33	0.12	6.50
MO	0.00	0.08	0.33	0.14	2.00
VA	0.33	0.20	0.33	0.20	16.50
DE,DC,MD,WV	0.33	0.24	0.42	0.34	6.17
GA	0.00	0.15	0.00	0.13	18.50
NC,SC	0.17	0.22	0.17	0.24	8.75
FL	0.00	0.32	0.00	0.33	11.00
AL,KY,MS	0.22	0.10	0.22	0.11	5.67
TN	0.33	0.07	0.33	0.16	4.00
AR,LA,OK	0.22	0.13	0.22	0.14	4.00
TX	0.33	0.32	0.33	0.33	29.00
CO	0.00	0.31	0.67	0.42	16.50
ID,MT,UT,WY	0.25	0.25	0.25	0.25	5.50
AZ	0.33	0.13	0.33	0.30	23.00
NV,NM	0.42	0.32	0.50	0.35	15.75
CA	0.33	0.81	0.33	0.89	29.00
AK,HI,OR,WA	0.42	0.46	0.42	0.47	11.00

In addition to the RECS data, I also use the scores produced by the American Council for an Energy-Efficient Economy (ACEEE) to account for regional characteristics. ACEEE provides information on the state-level energy efficiency policies, and scores states based on the adoption and implementation of energy efficiency policies and programs. This score has been computed every year since 2006 for all 50 states and the District of Columbia. ACEEE uses eight categories to compose the 2008 scores, and one of them is “Financial and Information Incentives”, which measures the state financial incentives for energy efficient appliances and buildings. Six state policy areas are used to compose the 2009 ACEEE score. These ACEEE scores are used to control for the regional heterogeneity in energy conservation efforts. In addition to the regional energy efficiency policies, I also use the scores produced by the Alliance for Water Efficiency (AWE) on state-level water conservation efforts. The first and only AWE scores are produced based on the 2011 survey, and can be used to approximate the water conservation efforts at the time of the 2009 survey. The 2009 RECS data group some states together, creating 27 regions. Table 4 shows the descriptive statistics for these regions. The ACEEE scores are scaled based on the total score in each category.

4 Empirical Framework

This section discusses the empirical model I use to test the predicted relationships between Energy Star appliances and their frequency of use, and the identification strategy used to establish the impact of energy efficiency level on frequency of use.

4.1 Estimation Strategy

The first equation used to estimate the impact of energy efficiency level on the frequency of use is:

$$s_i = \alpha_1 + \beta_1 \eta_i + \gamma_1 X_i + \delta_1 R_r + \varepsilon_{1i}, \tag{13}$$

where s_i denotes the frequency of using the appliance in household i; η_i is a dummy variable indicating whether the appliance is Energy Star in household i; X_i is a vector of control variables including household demographics, energy using behavior and housing characteristics; R_r is a vector of regional characteristics or fixed effects; and ε_{1i} is an error term with mean zero.

Ordinary Least Squares (OLS) regression can be used to estimation equation (13) by treating the outcome variable as a continuous measure of frequency. However, the outcome variable here is in fact categorical and ordinal, which means the ordering of values is known but the distance between them is unclear (Williams, 2016). Hence, the assumptions of OLS might be violated due to truncated value and unequal distance between values. In addition, with different but equally valid labeling of values, OLS would generate different estimates. Ordered logit regression is often used when the outcome variable is discrete and ordinal. Instead of directly estimating a linear relationship, ordered logit regression treats equation (13) as the process of generating an underlying unobserved (latent) s_i that determines the categories of observed s_i^{obs}: $Pr(s_i^{obs} = j) = Pr(\kappa_{j-1} < s_i \leq \kappa_j)$, where $\{\kappa_1, ..., \kappa_{k-1}\}$ is a set of cutpoints that decide k possible outcomes in the distribution of the latent variable s_i. This method makes proportional odds assumption, which requires the same relationship between each pair of outcomes. If such assumption does not hold, one can use partial proportional odds model which relaxes the assumption for all variables or those variables where it is violated (Williams, 2016). Equation (13) is estimated separately for different appliances.

Because ownership of an energy efficient appliance is a choice made by the household, directly estimating equation (13) using a naive OLS or ordered logit regression is likely to lead to biased estimates due to unobserved heterogeneity, measurement error and reverse causality. The next section discusses the identification strategy used to address these issues.

4.2 Identification Strategy

The households that choose to purchase Energy Star appliances are likely to differ from those who don't, such as having higher energy demand or being more environmentally conscious, their appliance using behavior is likely to differ for reasons other than the direct rebound effect. In order to correct such selection bias, I use an instrumental variable (IV), which is a variable that is correlated with the ownership of Energy Star appliances but arguable uncorrelated with the error term in equation (13). Two requirements must be satisfied to guarantee a valid IV. First, it must be correlated with ownership of Energy Star appliances, which is the relevance restriction. Tests of weak instrument can show whether this condition is met. Second, it must only affect the frequency of use through the Energy Star status of these appliances, which is the exclusion restriction.

The IV that I use to identify the relationship between ownership of an Energy Star appliance and its frequency of use is the regional share of households that have the Energy Star appliance in question. The identifying assumption is that the region-level percentage of households owning the Energy Star appliance should be uncorrelated with the error term in the individual household decision on the frequency of use. Mathematically, the regional-level percentage should be uncorrelated with ε_{2i} in equation (14)

$$s_i = \alpha_2 + \beta_2 \hat{\eta}_i + \gamma_2 X_i + \delta_2 R_r + \varepsilon_{2i}. \tag{14}$$

$\hat{\eta}_i$ is the predicted value of η_i obtained from the first-stage regression:

$$\eta_i = \alpha_3 + \theta p_r + \gamma_3 X_i + \delta_3 R_r + \upsilon_{3i}, \tag{15}$$

where p_r is the percentage of households owning the Energy Star appliance in region r and υ_{3i} is an error term with mean zero. If the instrumental variable p_r is uncorrelated with ε_{2i} but partially correlated with η_i, then the coefficient β_2 is the local average treatment effect (LATE). It is interpreted as the effect of having an Energy Star appliance on the frequency of use for those who were induced to buy one in regions where the Energy Star appliance ownership is high. According to Angrist and Pischke (2008), Two Stage Least Squares (2SLS) captures LATE regardless of whether the dependent variable is continuous or discrete. Moreover, assumption on the distribution of latent error term is needed for identifying average causal effect using logit or probit regressions. Hence, 2SLS is used to estimate the causal relationships between energy efficiency status and frequency of use.

The regional share of households owning an Energy Star appliance is calculated as the number of households having the Energy Star appliance (e.g., dishwasher) divided by the total number of households that have the appliance (e.g., dishwasher) in region r. This variable is unlikely to be correlated with the error term ε_{2i} in equation (14), such as the environmental awareness of individual households. Although it is possible that households in the same region are driven to adopt Energy Star appliances because of the potential energy savings, this is unlikely to directly affect the dependent variable, which is the frequency of using the appliance instead of energy savings. In the regions that have a higher share of Energy Star appliance ownership, households are expected to have a higher probability of purchasing an Energy Star appliance. This could be due to regional incentives for purchasing Energy Star appliances or peer effects. Section 5.3 discusses the possibility of using the state-level ACEEE policy score as an IV. I show that the ACEEE policy scores do not meet the relevance restriction because they are not statistically significant factors in the household decision to purchase Energy Star appliances in the sample. A household may also be more likely to purchase an Energy Star appliance if their neighbors, friends or relatives have purchased one. In order to identify a weighted average of individual causal effects, the effect of the IV on the endogenous regressor must be monotone (Angrist and Pischke, 2008). This means while not all households decided to purchase Energy Star appliances because of peer effects, those who are affected by peer effects should be affected in the same way. Literature on peer effects usually identifies monotone impact on individual behavior. Examples include students generally benefit from high peer performance in test (Sacerdote et al., 2011; Pivovarova, 2013), and households are more likely to install solar panels if their neighbors installed solar panels (Bollinger and Gillingham, 2012a). In addition, it is unlikely that a household decides not to purchase Energy Star appliance because their peers have Energy Star appliances. Therefore, the estimated LATE can be interpreted as the impact of having Energy Star appliances on the frequency of use among the households who were induced to buy Energy Star by peer effects.

One might suspect that the regions with higher Energy Star ownership rate are likely to have other policies in place to encourage energy and resource conservation. To address this concern, I add regional incentive policy scores, including the ACEEE scores and Water Efficiency and Conservation (AWE) score, as control variables in the first and second stage regressions.

In addition to unobserved heterogeneity, there are two more potential sources of statistical endogeneity: reverse causality and measurement error. It is entirely possible that households that plan to use their appliances more frequently choose more efficient appliances. In fact, in the theoretical model, the household takes into account the future demand for the appliance service when choosing the optimal level of energy efficiency to invest in. This IV is still plausibly exogenous to the individual household's frequency of using the appliance, because it is unlikely that an individual household's preference would affect the number of households having Energy Star appliances in that state or the neighboring states. Regarding measurement error, it is possible that the respondents provided inaccurate answers when asked about the frequency of using their appliances. Therefore, this paper focuses on the impact of having Energy Star appliances on the *reported* frequency of use. In Section 5, the impacts on electricity consumption of having Energy Star appliances are also estimated. The data on energy consumption are collected from the electricity suppliers by the EIA based on the billing information provided by the household respondents. The energy supplier survey is mandatory for all utilities, municipalities and cooperatives, and the data are subject to rigorous edits by the EIA to ensure data quality. Hence, measurement error is less likely to occur for the data on electricity consumption (EIA, 2013) .

5 Results

5.1 Estimation Results

Table 5: OLS estimation results for the frequency of using dishwasher

	(1)	(2)	(3)
Energy Star Dishwasher	0.281**	0.239**	0.255**
	(0.088)	(0.084)	(0.086)
Constant	3.175***	1.767***	1.366**
	(0.082)	(0.406)	(0.438)
Observations	1761	1761	1761
Adjusted R^2	0.006	0.195	0.200
Controls	No	Yes	Yes
Regional Dummies	No	No	Yes

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 6: Ordered logit estimation results for the frequency of using dishwasher

	(1)	(2)	(3)
Energy Star Dishwasher	0.420**	0.401**	0.451**
	(0.131)	(0.143)	(0.146)
Observations	1761	1761	1761
Controls	No	Yes	Yes
Regional Dummies	No	No	Yes

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Tables 5 and 6 show the OLS and ordered logit regression results with Huber/White/sandwich robust standard errors respectively. Both models show that dishwashers with Energy Star labels are associated with higher frequency of use across specifications. Interpretation of coefficients from the ordered logit regression is robust to different labeling of the frequency variable: holding other variables constant, for a one unit increase in “Energy Star Dishwasher”, i.e., going from 0 to 1, the log odds of being in a higher level of frequency category increases by 0.401 (Table 6, specification 2). Brant tests show that the variable “Energy Star Dishwasher” satisfies proportion odds assumption, while some control variables violate this assumption at 5% significance level.

Table 7: 2SLS estimation results for the frequency of using dishwasher

	(1)
Energy Star Dishwasher	-1.409
	(0.835)
Constant	2.782***
	(0.658)
Observations	1761
R^2	0.032
F-statistic (Weak Instrument Test)	21.770
Durbin chi-squared statistic (Endogeneity Test)	4.785
Durbin chi-squared p-vaule (Endogeneity Test)	0.029
Wu-Hausman F statistic (Endogeneity Test)	4.729
Wu-Hausman F statistic p-value (Endogeneity Test)	0.030

Standard errors in parentheses
* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Partial proportional odds model is used to relax the assumption for those variables violating it. Full OLS and ordered logit regression results are in B.2.

The association found using OLS and ordered logit does not imply that the households use dishwashers more often because the dishwashers are Energy Star. Table 7 presents the 2SLS estimates of the impact of having an Energy Star dishwasher on the frequency of use. The 2SLS estimator is statistically significant only at 10% level and the F-statistic on the IV exceeds the threshold of 10 set by Stock and Yogo (2002) for an IV not to be considered weak. After accounting for the endogeneity of the Energy Star ownership status, the IV estimates show that having an Energy Star dishwasher is likely to reduce the frequency of use by 1.4 (statistically significant at 10% level, but not at 5% level), given the current frequency labeling. As suggested by Angrist and Pischke (2008), I run a diagnostic regression of the dependent variable on the IV, which presents the reduced form regression of the frequency of using dishwasher on its Energy Star status. The reduced form relationship between the IV and the dependent variable is also negative and significant only at the 10% level, but not at 5% level, which is consistent with the 2SLS estimation. The detailed results of the first stage and the full IV regression and the reduced form regression are presented in B.2. This result is consistent with the theoretical prediction that there is likely to be a negative direct rebound effect for Energy Star dishwashers. The first stage regression results provide some insights on the factors associated with higher likelihood to purchase Energy Star dishwashers, such as living in a rural area, having other Energy Star appliances, high electricity price, and owning a house. In contrast to the findings in Murray and Mills (2011), I did not find a statistically significant relationship between the regional ACEEE score and the likelihood of purchasing Energy Star appliances. This might due to the lack of consumer participation in the incentive programs for Energy Star appliances. In the 2009 RECS, only 11.85% of the households that own Energy Star dishwashers reported to have used any rebates, tax credits or loans to assist with their purchase, and that number for Energy Star room air conditioners is only 0.2%.

Table 8: OLS estimation results for the frequency of using room air conditioner

	(1)	(2)	(3)
Energy Star Room Air Conditioner	0.006	0.128	0.126
	(0.069)	(0.070)	(0.070)
Constant	1.694***	2.245***	2.085***
	(0.062)	(0.259)	(0.269)
Observations	907	907	907
Adjusted R^2	-0.001	0.112	0.116
Controls	No	Yes	Yes
Regional Dummies	No	No	Yes

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 9: Ordered logit estimation results for the frequency of using room air conditioner

	(1)	(2)	(3)
Energy Star Room Air Conditioner	0.006	0.316	0.294
	(0.158)	(0.177)	(0.178)
Observations	907	907	907
Controls	No	Yes	Yes
Regional Dummies	No	No	Yes

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 10: 2SLS estimation results for the frequency of using room air conditioner

	(1)
Most Used Energy Star Room Air Conditioner	0.483
	(0.550)
Constant	2.010***
	(0.451)
Observations	907
R^2	0.115
F-statistic (Weak Instrument Test)	14.952
Durbin chi-squared statistic (Endogeneity Test)	0.432
Durbin chi-squared p-vaule (Endogeneity Test)	0.511
Wu-Hausman F statistic (Endogeneity Test)	0.418
Wu-Hausman F statistic p-value (Endogeneity Test)	0.518

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Tables 8, 9 and 10 provide the analogs of Tables 5, 6 and 7 for room air conditioners. Both the OLS and ordered logit results show room air conditioners with Energy Star labels are weakly associated with higher frequency of use (statistically significant at 10% level), while 2SLS estimates provide no evidence of a significant effect.[12] The reduced form regression between the IV and the frequency of using air conditioner also shows a statistically insignificant relationship. Hence, the sign of the direct rebound effect is ambiguous in the case of room air conditioners. The complete OLS, ordered logit and IV regression results are presented in B.3.

5.2 Impacts on Energy Consumption

How does the direct rebound effect affect the energy savings from using more efficient appliances? Conceptually, holding other variables constant, a negative direct rebound effect should amplify energy savings as the appliance is more efficient and the household uses it less frequently. Similarly, a positive direct rebound effect would offset energy savings as the households use the efficient appliance more frequently. However, as energy efficient appliances reduce the energy consumption of certain household tasks, real income increases, which encourages the household to increase consumption of other goods and services. Such an impact on other goods and services is often referred to as an "indirect rebound effect". Estimating the influence of the direct rebound effect on energy savings is likely to be confounded by the presence of an indirect rebound effect. For example, while a negative rebound effect in using an Energy Star dishwasher amplifies its energy savings, it is possible that the household increases energy consumption in other activities, which would offset the estimated energy savings from using Energy Star dishwasher. Nonetheless, it is informative to look at the impact of Energy Star appliance ownership on electricity consumption, because saving energy is the ultimate goal of energy efficiency programs and the results also provide robustness checks on the estimated direct rebound effect.

The OLS regression result in Table 11 shows a negative and statistically significant association (at 10% level) between having an Energy Star dishwasher and electricity consumption excluding space heating, water heating, space cooling and refrigeration in 2009. The 2SLS regression results in Table 12 confirm that Energy Star dishwashers in fact reduce electricity consumption (also at 10% level). These results are consistent with the negative direct rebound effect identified in the

[12] The Durbin-Wu-Hausman test indicates that the null hypothesis of exogeneity cannot be rejected, but this does not guarantee the Energy Star status of the most used room air conditioner is completely exogenous.

previous section. Both the OLS and the 2SLS estimated coefficients are large in magnitude and have wide confidence intervals. This is likely due to the reduced electricity consumption of appliances and services other than Energy Star dishwashers. It is possible that after purchasing Energy Star dishwashers, some households decide to adopt more energy efficiency measures, which would result in the large estimated energy savings. The full regression results are presented in B.4.

Table 11: OLS estimation results for electricity consumption

	(1)
Energy Star Dishwasher	-405.995
	(222.908)
Constant	-2054.007*
	(972.466)
Observations	1761
R^2	0.629

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 12: 2SLS estimation results for electricity consumption

	(1)
Energy Star Dishwasher	-3586.457
	(2082.676)
Constant	43.976
	(1665.473)
Observations	1761
R^2	0.588
F-statistic (Weak Instrument Test)	23.818
Durbin chi-squared statistic (Endogeneity Test)	2.656
Durbin chi-squared p-vaule (Endogeneity Test)	0.103
Wu-Hausman F statistic (Endogeneity Test)	2.612
Wu-Hausman F statistic p-value (Endogeneity Test)	0.106

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Tables 13 and 14 show ambiguous evidence on the impact of having an Energy Star room air conditioner on electricity consumption. The OLS results show a positive association, while the IV regression does not provide evidence that having Energy Star room air conditioner affects the overall electricity consumption on space cooling. These results are also consistent with the ambiguous results on the direct rebound effect for Energy Star air conditioners. The full regression results are presented in B.5.

Table 13: OLS Estimation Results for Electricity Consumption

	(1)
Energy Star Room Air Conditioner	212.395*
	(92.537)
Constant	-376.082
	(319.029)
Observations	907
R^2	0.536

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 14: 2SLS estimation results for annual electricity consumption for space cooling

	(1)
Energy Star Room Air Conditioner	301.867
	(652.243)
Constant	-276.455
	(532.590)
Observations	907
R^2	0.603
F-statistic (Weak Instrument Test)	14.869
Durbin chi-squared statistic (Endogeneity Test)	0.030
Durbin chi-squared p-vaule (Endogeneity Test)	0.863
Wu-Hausman F statistic (Endogeneity Test)	0.029
Wu-Hausman F statistic p-value (Endogeneity Test)	0.866

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

5.3 Limitations

Previous studies usually use price elasticity to approximate the direct rebound effect and focus on one appliance or one type of energy service. In contrast, this paper directly estimates the direct rebound effect as the impact of higher energy efficiency on the frequency of use, and shows that the direct rebound effect varies by the type of energy service. That said, this paper uses Energy Star certification as a proxy for higher efficiency due to the lack of data on actual efficiency levels. Therefore, the empirical analysis in fact estimates household response to the Energy Star labels. Because the appliances need to meet the requirements established by the EPA to earn the certification, the Energy Star labels can arguably serve as a good proxy for high energy efficiency. Data on the appliance capacity would improve the analysis, since it is likely that capacity varies within the Energy Star certified appliances.

Admittedly, there might be unobserved regional characteristics that influence both the uptake of Energy Star appliances and the frequency of using appliances, which threatens the validity of the regional IV. One might suggest to use the state or utility level financial incentives that promote Energy Star appliances. There is some evidence suggesting that government energy efficiency policies increase the probability of adopting energy efficient technology and appliances (Qiu, 2014; Nevo and Rosen, 2012). A common way to measure the level of energy efficiency policies in the U.S. is the ACEEE policy score (Qiu, 2014; Murray and Mills, 2011). This variable was considered as an IV, but did not pass the weak instrument tests (see B.6). Several methods can be used to potentially improve the causal identification in this analysis. Nevo and Rosen (2012) propose a method to estimate analytic bounds for coefficients when the IV is not strictly exogenous, and is correlated with the error term in the same way as the correlation between the endogenous regressor and the error term. Another alternative is to use a difference-in-difference design that surveys the respondents before and after the purchase of an Energy Star appliance. Unfortunately, the RECS does not provide such data.

Another potential threat to the internal validity of the results is a violation of the stable unit treatment value assumption (SUTVA or "no spillovers"). In this context, SUTVA requires that whether one household purchases an Energy Star appliance or not should have no impact on another household's frequency of using their appliance. Although the identification strategy utilizes the peer effect phenomena in the adoption of Energy Star appliances, it is unlikely that the frequency of using dishwasher and air conditioner in a household is influenced by another household's appliance choice.

Regarding external validity, the sample in the analysis allows me to draw inferences on the direct rebound effects among the households that had replaced dishwashers or air conditioners between 2005 and 2009, were aware of the Energy Star labels and paid their own electricity bills at the time of survey. It is unclear whether the results apply to other Energy Star appliances or households that are not aware of the program or households who do not pay their own electricity bills.

6 Conclusions

This paper conceptually and empirically shows that the direct rebound effect varies by the type of energy efficient appliance. An Energy Star dishwasher, which meets basic living needs and requires additional labor input to operate, leads to a lower frequency of use and hence a negative direct rebound effect. An Energy Star room air conditioner, which also meets the basic living needs but does not require labor input to operate, might result in the same or high frequency of use. The estimated impacts of Energy Star appliances on electricity consumption show that the negative direct rebound effect is likely to amplify energy savings, while the positive direct rebound effect is likely to offset energy savings, rendering no change or an increase in electricity consumption.

Several policy implications can be drawn from these findings. First, agencies can take into account the heterogeneous direct rebound effects when evaluating energy efficiency programs. Program impacts can be large for the energy efficient appliances with negative direct rebound effects. Program impacts might be small or zero when there are positive direct rebound effects. Overestimating the program impact on energy savings might lead to the lack of supporting policies. Underestimating the impact might undermine the priority of effective energy conservation programs. Second, the 2SLS regression shows that state level incentive policy scores, which consider rebate and tax credit programs, do not have strong predictive power for the uptake of Energy Star dishwashers and room air conditioners. More research is needed on the effectiveness of these incentive policies at promoting Energy Star appliances.

Chapter 3. Heterogeneous Impacts of Residential Solar Rebate Programs in the U.S.

Abstract

Financial incentives such as rebate programs have played important roles in promoting solar energy adoption. Understanding the heterogeneity in program effectiveness can help policy makers better target program recipients and assist with program implementation to maximize impact. In this chapter, I combine inverse propensity score weighting with causal forests, a novel machine learning method, to empirically examine the varying treatment effects of residential solar rebate programs in the U.S. Using zip code-level panel data between 2008 and 2015, I find a positive average treatment effect on annual residential solar installation capacity with significant heterogeneity across observations. The percentage of renewable energy mandated by Renewable Portfolio Standards is associated with high effectiveness of rebate programs and plays a significant role in explaining the heterogeneity. Market characteristics, such as residential electricity rate, cost of solar installations as well as community solar capacity, also play important roles. Important demographic factors are county level median house value, median income level and population density. Relationships between treatment effect and important explanatory factors display significant non-linearity. These findings suggest that legislative goals are more likely to support rebate programs than other types of solar policies, and certain solar market characteristics are indicative of high program effects.

Keywords: solar rebate programs, heterogeneous treatment effects, machine learning

1 Introduction

In recent years, the U.S. has experienced impressive growth in its solar photovoltaic (PV) sector. Over the last decade, total installed solar capacity grew at an average annual rate of 59%, generating enough electricity to power over 10.1 million homes (Solar Energy Industries Association, 2018). The residential solar PV sector had above 50% annual growth rate for many years, and its capacity accounted for over half of new solar installation in 2017 (Solar Energy Industries Association, 2018). To mitigate global warming and facilitate the transition to sustainable energy systems, federal and state governments have played significant roles in promoting residential solar installations through a myriad of policies. Studies have shown that rebate programs, which offer subsidies towards installation costs of solar PV systems, usually in terms of dollar per watt of installation capacity, are effective at promoting residential solar installations (Sarzynski et al., 2012; Hughes and Podolefsky, 2015; Crago and Chernyakhovskiy, 2017).

In this paper, I explore more nuanced questions about program effectiveness: Does a program with positive average treatment effect benefit everyone? Under what conditions does a program generate positive and large treatment effects? Understanding how different subpopulations benefit from an incentive program can help policy makers better target recipients and maximize its impact. Insights on how treatment impacts vary with the existence of other policies also help with effective implementation.

To address these questions, I use causal forests, a novel machine learning method developed by Wager and Athey (2017), to empirically examine how the effectiveness of residential solar rebate programs varies by other policy and non-policy factors, and identify the conditions under which rebate programs lead to high residential solar installations. Zip-code level panel data spanning nine years (2007 - 2015) for 36 states are constructed from multiple data sources. Treatment effects are causally identified using inverse propensity score weighting, where the propensity score is estimated using a generalized boosted model. Causal forests generate an estimated treatment effect for each observation, which allows in-depth analysis on the distribution of these effects.

The innovation of this paper lies in the application of machine learning methods in evaluating residential solar policies in the U.S. The results show the conditions in which solar rebate programs perform well (or not well) and how to effectively target sub-populations to increase policy impact. In addition, I estimate the impacts of residential solar policies based on a panel dataset from a large number of states, whereas previous studies mostly focus on California or a smaller region in the U.S.

The results show significant heterogeneity in rebate program impacts, ranging from -254.35 to 944.93 kW of added solar PV capacity by zip code region by year. The percentage of electricity generation from renewable energy sources mandated by Renewable Portfolio Standards plays an significant role in explaining the heterogeneity, while the percentage of solar carve out in Renewable Portfolio Standards, which requires certain portion of the renewable source to be solar, is less important. Market characteristics, such as residential electricity rate, cost of solar installations as well as community solar capacity, also have high explanatory power. Important demographic factors include county level median house value and median income level. Significant nonlinearity exists in the relationships between treatment effect and these factors. These findings suggest that legislative goals are more likely to support rebate programs compared to other types of solar policies, and certain solar market characteristics are indicative of high program effects.

This paper contributes to the growing body of empirical literature examining the determinants of increased residential solar PV capacity. Most previous studies focus on the effectiveness of one specific policy, such as Solar Renewable Energy Credit (Burns and Kang, 2012), Renewable Portfolio Standards (RPS) (Carley, 2009) and California Solar Initiative subsidy program (Dong and Rai, 2014; Hughes and Podolefsky, 2015). Some have looked at the impacts of groups of policies, including state-level financial incentives and market support policies (Sarzynski et al., 2012; Krasko and Doris, 2013; Crago and Chernyakhovskiy, 2017). Other have studied non-policy factors that affect residential solar adoption, such as peer effect (Bollinger and Gillingham, 2012b) and demographic characteristics (Sommerfeld et al., 2017). Overall, these studies find financial incentives and market support policies, such as interconnection standards and net metering policies, are significant in explaining state-wide solar installation uptake.

Most of the prior empirical analyses overlook the interactions among policies and non-policy factors. Multiple policies are often implemented simultaneously and limited empirical studies show they are likely to influence each other. For instance, a combination of well-designed interconnection and net metering standards has been shown to provide good support for distributed generation PV systems (Krasko and Doris, 2013). The order in which different policies are enacted also matters. For example, financial incentives for distributed generation PV would only work if interconnection agreements are set in advance (Krasko and Doris, 2013). In addition, demographic characteristics can affect policy impact. Sommerfeld et al. (2017) show the key demographic determinant shifted from family size to dwelling size after the feed-in tariffs ended in Queensland, Australia. However, we often do not have a complete understanding of how policies interact with each other, or interact with other non-policy factors. In empirical analyses, imposing structural models with a set of predetermined interaction terms might yield misleading results. The approach used in this chapter addresses this issue and generates policy insights from these interactions.

The rest of this paper is organized as follows. Section 2 reviews the theoretical literature on solar PV adoption and solar policies. Section 3 briefly reviews the causal regression tree method proposed by Athey and Imbens (2016) and causal forest developed by Wager and Athey (2017). Section 4 describes data sources and presents descriptive statistics of the dataset. Section 5 describes the identification strategy used to causally estimate treatment effects. Section 6 presents the estimation results and analyzes the distribution of heterogeneous treatment effects. Section 7 concludes and discusses policy implications.

2 Theories on solar PV adoption and policies

The adoption of solar PV technology has been studied from several different perspectives, two of which are commonly used by economists. The first strand of literature focuses on the economic rationale of adopting PV systems as an alternative energy generating source. A large body of it examines the factors influencing the cost-effectiveness and investment uncertainties of solar PV technologies (Ansar and Sparks, 2009; Sarzynski et al., 2012; Bauner and Crago, 2015). Solar PV installations require high up-front costs, but do not require fuel inputs to generate electricity. Hence, its relative cost competitiveness against conventional energy sources, such as fossil fuels, depends on initial upfront system costs, current electricity rates and price and reliability of solar electricity generated over the system's life cycle. Early studies focus on the high upfront system costs and the low prices of competing energy sources as barriers to adoption (Bezdek et al., 1979; Scarpa and Willis, 2010). In a more recent study, using option value theory, Bauner and Crago (2015) show that uncertainty in energy prices and PV technology has significant impact on the timing of investment in residential PV, and households would require higher rate of return for the PV investment to occur. Therefore, financial incentives, such as rebate, tax credits and feed-in tariffs, that aim to reduce upfront costs and alleviate uncertainties, are important for increasing PV technology's relative competitiveness.

In addition, some economists regard the slow adoption of solar PV as the result of market failures, which include environmental externality of conventional fuels and spillover benefits from learning by doing (Painuly, 2001; Van Benthem et al., 2008; Dong and Rai, 2014). Externality and market failures also provide economic justification for the use of regulatory instruments to reach socially optimal solar adoption level.

The second set of literature is based on the technology diffusion model, which considers the adoption of solar PV technology as a social process that involves demographic factors, personal perception of risks and uncertainties among early adopters, and information dissemination through social networks (Schelly, 2014). The theory categorizes consumers based on when they choose to adopt the new technology: innovators, early adopters, early majority, late majority and laggards (Rogers, 2010). The speed of the diffusion process is affected by the innovativeness of early adopters, the consumer perception of the technology's advantages over alternatives and its compatibility with current lifestyle, as well as communication channels (Wolske et al., 2017). Empirical studies are done to identify the characteristics of early adopters, including being younger, being more educated and perceiving PV technology less financially and socially risky (Faiers and Neame, 2006; Wolske et al., 2017). Social interaction, or peer effect, plays an important role in the diffusion of solar PV technology (Bollinger and Gillingham, 2012b; Rai and Robinson, 2013). Despite the fast overall growth rate of residential solar, in many markets the process is still at early adoption stage. Policies that incentivize and stimulate early adoption, reduce risk perceptions and promote awareness about the benefits of solar PV can strongly accelerate the diffusion process.

These theories show that policies and incentives are important for promoting solar adoption, and provide foundation for policy design and evaluation. Compared to the large amount of literature on solar adoption decision, less work is done providing theories on how policies work to achieve their goals. Krasko and Doris (2013) create a policy-stacking framework and identify strategies for implementing cost-effective policies in sequence to generate maximum effects. Specifically, they group solar related policies into three categories: market preparation, market creation and market expansion. Market creation policies include interconnection and net metering standards, and they aim to remove institutional barriers to prepare the market for emerging technologies. Market creation policies, such renewable portfolio standards (RPS), reduce uncertainties for solar developers and investors by making long-term public commitment to renewable energy sources, creating demand and increasing confidence. Market expansion policies, such as financial incentives, help reduce up-front costs of investment and stimulate adoption of new technologies. These policies are stacked in the way such that market preparation lays foundation for market creation and expansion policies, and market creation policies set stage for expansion policies to work. Hence, the order in which different policies are enacted is important, and the quality of one policy influence the effectiveness of other policies (Krasko and Doris, 2013). Some studies also model the incentive pass-through mechanism, which examines how much financial incentives are passed to consumers through suppliers (Wolfram, 1999; Dong and Rai, 2014).

Despite the ample literature on household solar adoption, there is limited conceptual understanding and empirical investigation on how policies influence solar adoption behavior and how policies interact with each other. Imposing structural assumptions on these relationships when examining empirical evidence might yield misleading results and overlook unexpected relations. Machine learning methods, with their advantages in data mining, can help us uncover some of these inter-relationships and gain better understanding on how to improve policy effectiveness.

3 Causal trees and forests

Traditionally, identifying heterogeneous treatment effects requires researchers to pre-specify interactions terms or sub-populations in which they expect the programs might perform differently. These approaches require researchers to have enough knowledge or make assumptions about how the program interacts with other variables. Although conceptual models can help us make hypotheses on how the program works, the range of potential heterogeneity is usually large enough that testing all possibility is unattainable. Strong but unexpected treatment effect heterogeneity is difficult to uncover using pre-specified functional forms.

Athey and Imbens (2016) develop a data-driven approach to explore heterogeneous treatment effect by combining causal inference with regression tree, a machine learning method. Classification and regression tree (CART) is a commonly used data mining tool that predicts values of an outcome variable based on a set of covariates (Watkins et al., 2013). Classification trees are for binary outcome variables and regression trees are for continuous outcome variables. It analyzes the interrelations between covariates and outcome variables by repeatedly splitting the sample in half. In each split, CART chooses a predictor variable and a value to split on, and fits the resulting two subsamples (i.e. “leaves”) to a simple model, such as average outcome or the most probable binary outcome (Friedman et al., 2001). The splitting process continues until certain stopping rule is reached, such as minimum prediction error reduction (Friedman et al., 2001). Cross validation is often used to select the best tree size with minimum out-of-sample prediction errors. It is done by using a training sample to grow a tree and test its prediction error in a test sample, and finding the tree with the lowest prediction errors (Friedman et al., 2001).

Athey and Imbens (2016) make use of the recursive splitting property of CART and have it partition the average treatment effect instead of the outcome variable. Assuming unconfoundedness, which states that treatment status is independent from potential outcome conditioning on covariates, they replace average outcome in each leaf with an unbiased estimator of average treatment effect, and have the algorithm minimizes the sum of squared prediction error:

$$\sum_i (\hat{\tau}(W_i) - \tau(W_i))^2, \tag{16}$$

where $\hat{\tau}(W)$ is the unbiased estimated treatment effect and $\tau(W)$ is the real treatment effect, conditioning on a set of covariates W_i. Identification strategy used to obtain $\hat{\tau}(W)$ is discussed section 5.

They also propose "honest" causal regression tree, which addresses overfitting concerns in adaptive methods. This approach uses one sample to build and cross-validate the tree, and another to estimate treatment effect for each subpopulation. It essentially treats the partition as given when estimating treatment effect within each leaf, which preserve their asymptotic properties (Athey and Imbens, 2016). Athey and Imbens (2016) show that the objective of the algorithm is to minimize the expected mean squared prediction error, which is equivalent to maximize

$$Q \equiv E[\tau^2(W_i) - E[Var(\hat{\tau}(W_i))]]. \tag{17}$$

Let S^{tr} denote a training subsample and S^{est}an estimation subsample randomly selected from the original sample S. Q can be estimated by

$$\hat{Q} \equiv \frac{1}{N^{tr}} \sum_{i \in S^{tr}} \hat{\tau}^2(W_i) - (\frac{1}{N^{tr}} + \frac{1}{N^{est}}) \cdot \sum_{l \in \prod} \left(\frac{Var(Y)_{S^{tr}_{R=1}}(l)}{p} + \frac{Var(Y)_{S^{tr}_{R=0}}(l)}{1-p} \right), \tag{18}$$

where $\tau(W_i)$ is the in-leaf treatment effect and $\hat{\tau}(W_i)$ is the estimated treatment impact given covariates W_i; $Var(Y)_{S^{tr}_R}(l)$ is the within-leaf variance of outcome Y for the treated ($R = 1$) and control ($R = 0$) observations in leaf l from the tree $\prod$; N^{tr} and N^{est} are the number of observations in training and estimation subsamples, respectively. For cross validation, the same expression is used, but with cross-validation sample $S^{tr,cv}$.

Causal regression trees are built upon randomly selected training and test samples. Therefore, results from one single causal tree might be subject to spurious splits and outliers. Breiman (2001) shows that averaging predictions from many well-built trees often generates better results compared to a single highly optimized tree. In addition, it is not often clear what the "optimal" causal tree is (Wager and Athey, 2017), so aggregating multiple trees can reduce variance and smooth sharp decision boundaries (Büchlmann and Yun, 2002). Wager and Athey (2017) develop causal regression forest, which aggregates an ensemble of causal trees by averaging their predictions. This method generates "personalized" estimation of treatment effect for each observation instead of subpopulations, and provides valid confidence intervals for each estimated effect for statistical inference. Assuming unconfoundedness, causal forests generate unbiased and consistent estimators of treatment effects, and the variance of an estimator is estimated using infinitesimal jackknife (Wager and Athey, 2017). Compared to a single honest causal tree, honest forests make use of all observations in the sample instead of only half of the sample to build trees, because it re-randomizes the training and estimation subsamples in each iteration, so each data point is used for both specifying tree structure and treatment effect estimation (Wager and Athey, 2017).

There are several advantages of regression trees and forests over linear regression models in this application. First, when we need to consider higher order interactions and account for the hierarchy of interactions, linear models that attempt to capture these relationships can become extremely complicated. Obtaining the correct specification requires researchers to have sufficient knowledge of the underlying data generating process. Regression trees and forests can identify the most important interactions through recursive partitioning and select the optimal model by cross validation (De'ath and Fabricius, 2000). Second, linear regression models are sensitive to collinearity, where two covariates are highly correlated. Regression trees and forests use stepwise linear regression technique that searches through all possible combinations of covariates and picks a subset of least correlated variables, hence minimizing the impact of multi-collinearity (Huang and Townshend, 2003). Although these machine learning methods are not immune to collinearity because collineared covariates might be dropped from the model, Dormann et al. (2013) found that machine learning methods consistently outperform in prediction accuracy compared to linear models.

On the other hand, most machine learning methods, including causal trees and forests, are sometimes considered as "black-boxes" because they generate functional forms that are hard to interpret and analyze. Some researchers have used machine learning methods, such random forests, to identify a list of relevant factors and their interrelationships, and then fit them into a simple parametric model (Strobl et al., 2009).

4 Data and descriptive statistics

To quantify heterogeneous impacts of solar rebate programs on residential solar capacity at the zip code level, I construct a panel data of 6,903 zip codes in 36 states covering nine years from 2007 to 2015 from various data sources. The final dataset has 30,696 observations. This section describes the variables used in the empirical analysis and their data sources.

The primary data source is the National Renewable Energy Lab (NREL) Open PV project, which collects information on location, installation capacity, total installed cost prior to receipt of any incentives, rebate amount, name of the utility, as well as annual solar insolation (kWh/m2/day) for solar PV projects in the U.S. (NREL, 2012). The complete Open PV database contains about 78% of solar PV projects in the U.S. (NREL, 2012). The majority of the data are contributed by the Lawrence Berkeley National Laboratory, and the rest are contributed by members of the PV community, including installers, businesses and consumers (NREL, 2012). In this study, I only consider residential solar installations with size under 20 kW to exclude installations too large to be considered rooftop solar.

The outcome variable, capacity of solar installations added, as well as the treatment variable, whether having solar rebate program, are obtained from this data source. Some rebate programs have limits on system size eligible for rebate claims (e.g. Austin Energy Residential Solar PV rebate program requires eligible solar systems to be between 1 kW and 10 kW) or limits on the total amount of rebate that can be claimed (e.g. Energy Trust of Oregon provide rebates to residential solar PV installations up to $2100 per home for Portland General Electric utility customers and up to $1500 per home for Pacific Power utility customers). The disaggregate the effect of rebate program cap and per unit rebate level, I first collect data on the maximum rebate level in a zip code region because most rebate programs have caps on total amount of rebate available for a single project. I then calculate the rebate level ($/kW) for each project as the total amount of rebate received divided by the system size, provided that the total rebate amount is smaller than the program cap, and average that across all the solar projects in a zip code region.

In addition to the outcome and treatment variables, additional variables related to policies, electricity and solar market, and demographic characteristics are collected as control variables and are also used to explore how they the distribution of heterogeneous treatment effects.

Interconnection standards and net metering policies are considered as "market preparation" policies by Krasko and Doris (2013). The former outlines the procedures and legalities of connecting rooftop solar systems to the grid, including the limit on system capacity, certification and technical screening procedures, and standard agreements between customers and utilities (Krasko and Doris, 2013). The latter creates compensation systems for feeding generated solar electricity back into the grid once the interconnection process is complete (Krasko and Doris, 2013). Freeing the Grid (FTG) project produces annual reports that assess the interconnection and net metering standards of all states since 2007, and give a letter grade (from A to F where A is the highest score) to each state based on whether the existing policies can help increase distributed generation capacity (Freeing the Grid, 2017). The rating criteria for both standards include the eligibility of technologies, sectors and utilities, as well as system capacity limit for connection (Freeing the Grid, 2017). In addition to these criteria, the net metering score also takes into account whether net excess generation is credited to next billing cycle, the ownership of resulting renewable energy credits, as well as whether meter aggregation is allowed (Free the Grid, 2017). The letter grades of both standards for each state are collected and converted to numerical value for econometric analysis.

RPS have received a lot of attention in recent research on renewable energy and are considered as "market creation" policies that indicate long-term public commitment, create demand and reduce investment uncertainty (Krasko and Doris, 2013). They are state-mandated programs that require a certain percentage of overall electricity generation to come from renewable energy sources, and utilities under an RPS program need to invest in renewable energy systems to meet these requirements (Carley, 2009). In order to promote solar power generation, some states amend their existing RPS with a solar "carve-out", which requires certain percentage of renewable electricity coming from solar energy. Information on RPS and solar carve-out is collected from the National Conference of State Legislature (2017). The variables collected include whether a RPS program is in place, the required percentage of renewable energy, the establishing and ending year of the RPS, whether the RPS has solar carve out, the percentage of the solar carve out and the ending year of the solar carve out. Some states, such as Texas and Iowa, set goals in terms of Mega Watt of generation capacity, and these goals are converted to percentage of total current generation capacity to unify the metric.

Data on several other state-level solar policies are from the Database for State Incentives for Renewables and Efficiency (DSIRE). This database contains information on renewable energy related incentives and policies in the U.S., and I use the Solar Renewable Energy Credits (SRECs) and production tax credit. SRECs offer production credits to owners of grid connected solar systems based on the amount of electricity produced. Utilities can purchase SRECs to meet their solar carve-out requirement if they choose not to build solar power facilities themselves. Production tax credit is a form of tax deduction based on the amount of solar energy produced by the system ($/kWh). These two policies are grouped together as a dummy variable indicating whether either of them exists in each zip code and each year.

Solar rights protect property owners' access to sunlight and determine whether they can install solar panels on their properties (Bronin, 2009). In some states, homeowners associations have the rights to prohibit the installation of solar energy devices. Solar rights regulation in general states that homeowners associations cannot prohibit solar installations, but reserve the rights to pose restrictions on size, location and placement on the installations. Information on solar rights regulation is collected from Community Associations Institute, and a dummy variable is created to indicate whether the state has solar rights regulation in that year (1 means homeowner associations cannot prohibit solar installations, 0 otherwise).

Third party financing is a popular financing solution that allows homeowners to adopt solar energy with lower installation and maintenance costs. It usually takes two forms: power purchase agreements (PPAs) and solar lease (EPA, 2018). In the PPA model, a customer does not pay installation cost of the system, the solar developer sells the electricity generated to the customer at a fixed, lower than utility rate and the customer uses the purchased solar power to offset their electric utility bills. In the solar lease model, a customer signs a contract with a solar developer and pays for the use of the solar panels over a period of time, rather than paying for the electricity generated. In both models, customers do not own the solar installations, hence cannot take advantage of tax incentives and rebates. A dummy variable is created to indicate whether the state allows PPAs and solar lease. Information on third party financing is collected from EPA and state agency websites.

In addition to the residential solar PV related policies, I also collected information on alternative green energy policies. According to O'Shaughnessy et al. (2017), voluntary green power market accounts for around 28% of renewable energy sales in the U.S., excluding hydro power, and is experiencing rapid growth. Voluntary green power market allows retail electricity customers to purchase renewable electricity instead of generating themselves through several mechanisms, two of which are common among residential customers: utility green pricing programs and community solar (O'Shaughnessy et al., 2017). In green pricing programs, utilities typically procures green power and retires Renewable Energy Credits (RECs) on behalf of the customers with an added fee on their utility bills. Community solar program allows customers to subscribe to a shared solar project, usually large scale, and receive credits on their utility bills for the portion of solar power generated. These policies enable residential customers to renewable energy without physically installing systems on their properties, hence provide renewable power access to customers that cannot install PV systems, such as renters and homeowners with houses unsuitable for installations. Data on the number of customers in utility green pricing programs by state by year are collected from the EIA website (green pricing reports and form 861M). Information on the 2011 and 2015 green pricing customers is unavailable, hence is imputed using existing data[13]. Community Solar Hub provides the most up-to-date data information on the location and capacity of existing community solar projects in the U.S. As of 2018, there are 101 community solar projects with total capacity of 108 MW in the U.S. across 26 states. The aggregate community solar capacity as of 2018 is collected and used as a measure of community solar program efficacy.

Whether a state has deregulated utilities might also play a role in residential solar PV uptake. In deregulated states, customers can choose to buy from alternative electricity suppliers, while in regulated states, customers can only buy from their local utilities and the electricity rates are set by the commissions. In the literature, there is mixed opinion and evidence on the effect of deregulation status on renewable energy uptake. Some contend that deregulation increases market competition and enables product differentiation, hence encourage renewable energy development (Delmas et al., 2007). Empirical studies found that deregulation status has negative and statistically significant

[13] 2011 data is imputed as the midpoint between the 2010 and 2012 level; 2015 data is imputed using the 2014 data and the national customer growth rate in 2015 provided by O'Shaughnessy et al. (2017).

association with renewable capacity and power generation. The data on the deregulation status are collected from the website electricchoice.com. A dummy variable is constructed to indicate whether the state is deregulated (equal to 1).

Residential electricity rate by state by year is collected from the EIA (form 861M). County level demographic data is collected from the American Community Survey. The demographic variables included in the analysis are housing density, population density, median house value, median income level, percentage of bachelor degree and average household size.

Endowment of fossil fuels and wind energy might affect load serving entities' efforts to promote solar energy to meet their RPS, as well as the public attitude towards solar as an alternative energy source. Therefore, I include data on natural resource endowment at state level, which are the percentage of GDP from mining industry and wind energy capacity. The former variable is collected from the US Bureau of Economic Analysis (2017), and the mining industry includes oil and gas sector, which reflects fossil fuel endowment in that state. The data on wind power potential by state is from NREL. The variable is the potential installed capacity (MW) with 80 meter hub height and 2008 turbine technology in land area with 35% or higher gross capacity factor. The demographic variables and the GDP percentage from mining industry are disaggregated over time, while the wind power potential is constant over time in the final dataset.

Finally, I use the National Environmental Scores from the League of Conservation Voters (LCV) to measure the political climate toward environmental policies in each state over time. LCV produces an annual score card for each state documenting the annual average pro-environmental vote from all members of the House of Representatives and Senate (LCV, 2016). These scores reflect the environmental commitment of the state's legislative branch.

In order to account for unobserved factors affecting both solar installation uptake and rebate programs, I use dummy variables for years to account for the unobserved factors that are common across regions in a given year and changes in federal level policies, such as the federal production and investment tax credits. Other factors, such as the LCV conservation scores and natural resource endowment variables, are used to approximate unobserved heterogeneity across regions and time.

The final dataset is assembled from multiple sources. The sample only includes the zip codes with single serving utility to avoid spillovers and customers selecting into utilities with rebate programs.

Table 15: Descriptive statistics, N = 30,696

	Mean	Std. Dev.	Min.	Max.	Varies by
Outcome and treatment variables					
Added installation capacity (kW)	156.00	355.13	0.05	7547.19	Z,Y
Have solar rebate program	0.81	0.39	0.00	1.00	Z,Y
Incentive policies					
Rebate level ($/W)	1.00	1.07	0.00	10.42	Z,Y
Maximum rebate level ($)	41859	30063	0.00	193350	Z,Y
Have SREC or production tax credit program	0.38	0.48	0.00	1.00	S,Y
Number of customers in green pricing program	91847	200813	0.00	1644395	S,Y
Community solar garden capacity (kW)	4829	10470	0.00	44023	S
Regulatory policies					
Net metering score	4.64	0.99	0.00	5.00	S,Y
Interconnection score	3.82	1.22	0.00	5.00	S,Y
Solar rights regulation	0.65	0.48	0.00	1.00	S,Y
Third party ownership allowed	0.97	0.17	0.00	1.00	S,Y
Deregulated utilities	0.88	0.33	0.00	1.00	S,Y
Have RPS	0.99	0.10	0.00	1.00	S
RPS % (if RPS=1)	25.84	7.72	0.00	55.00	S
RPS ending year (if RPS=1)	2018.74	28.51	0.00	2026	S
RPS establishing year (if RPS=1)	2001.56	28.28	0.00	2011	S
RPS has solar carve out (SCO)	0.35	0.48	0.00	1.00	S
Solar carve out % (if SCO=1)	2.06	1.77	0.00	5.00	S
Solar carve out ending year (if SCO=1)	2020.43	5.20	2010	2027	S
Market characteristics					
Past year added capacity (kW)	109.13	255.35	0.17	5281.02	Z,Y
Year of installation	2012	2.13	2008	2015	Y
Average annual solar insolation (kWh/m2/day)	5.19	0.76	3.67	6.93	Z,Y
Cost of solar installation ($/W)	5.73	1.68	0.99	23.39	Z,Y
Residential electricity rate (cents/kWh)	15.37	2.60	7.57	37.36	S,Y
Wind energy potential (MW)	52284	241252	0.00	1418439	S
Demographic characteristics					
Housing density	536.22	1363.54	1.00	62406.25	C,Y
Population density	1144.41	2836.07	1.92	127114.30	C,Y
Median house value	314917	151758	64900	941400	C,Y
Median income ($/year)	63488	15167	30797	122068	C,Y
Bachelor degree or higher (%)	0.18	0.05	0.04	0.36	C,Y
Average household size	2.80	0.27	1.94	4.05	C,Y
GDP from mining industry (%)	0.05	1.12	0.00	40.00	S,Y
Senate environmental voting score	80.68	28.06	0.00	100	S,Y
House environmental voting score	65.01	18.70	1.00	100	S,Y

* The last column indicates the level of variation for each variable, where Z is for zip code region, C is for county, S is for state, and Y is for year.

Table 15 shows the descriptive statistics of the final dataset. The outcome variable is solar installation capacity added (kW) by year by zip-code region. The treatment variable is whether the region have solar rebate program in each year. Table 16 shows the distribution of observations across state, with California having the largest number of zip-code regions in the sample, while Maine, Mississippi and South Dakota only having on zip-code region in one year in the sample. It

Table 16: Distribution of observations across state, N = 30,696

State	Count	% of Obs.	% of Zip codes	State	Count	% of Obs.	% of Zip codes
CA	10018	32.64	58.01	VT	130	0.42	21.43
NY	4510	14.69	52.26	IN	54	0.18	2.61
NJ	3122	10.179	80.19	MN	46	0.15	3.32
MA	2351	7.66	72.25	UT	43	0.14	10.47
AZ	1698	5.53	52.29	RI	39	0.13	28.89
MD	1505	4.90	55.06	HI	26	0.09	18.25
CT	1467	4.78	65.18	WA	25	0.08	1.54
PA	1182	3.85	23.46	AR	14	0.05	1.70
TX	916	2.98	10.63	LA	13	0.04	1.67
NH	703	2.29	75.44	NM	11	0.04	2.58
WI	528	1.72	25.28	MI	7	0.02	0.52
NV	482	1.57	36.36	IA	6	0.02	0.38
OR	434	1.41	30.56	VA	5	0.02	0.33
DE	332	1.08	56.25	IL	3	0.01	0.19
OH	301	0.98	10.46	WV	3	0.01	0.24
FL	296	0.96	13.32	ME	1	0.00	0.21
MO	229	0.75	7.36	MS	1	0.00	0.19
CO	194	0.63	16.02	SD	1	0.00	0.26

also shows the percentage of zip codes included in the sample, addressing the fact that some states, such as California, have larger number of zip codes compared to other states, such as South Dakota. Due the voluntary reporting nature of the data, the sample is by no means nationally representative. That being said, identification strategies are developed to estimate causal impact of rebate program on adoption in the sampled regions. The large number of observations allow a detailed examination of its variation using machine learning method which I introduce in the next section.

5 Identification strategies

5.1 Inverse propensity score weighting

This section presents the empirical strategies used to estimate causal effects of solar rebate programs on the capacity of added residential solar installations. Specifically, Inverse Probability of Treatment Weighting (IPTW) method is used to address potential endogeneity and obtain unbiased estimator of treatment effects. In this paper, I focus on estimating the Average Treatment Effect for the Treated (ATT).

IPTW uses the probabilities of selecting into treatment, measured by propensity scores, as weights to create a pseudo-population in which the distribution of measured baseline covariates is independent from treatment status (Robins et al., 2000). This method accounts for confounders that are correlated with outcome variables and predicts selection into treatment. Regions that have rebate programs in place are more likely to be renewable-energy friendly and have other supporting policies in place for residential solar installations. These factors are correlated with the probability of creating rebate programs, and also directly affect the level of solar installations. These characteristics of residential solar market make it suitable to use IPTW to causally identify treatment impacts of solar rebate programs.

Let R_{it} denote the treatment status in zip code region i and time t. R_{it} is a dummy variable where 1 means having rebate program and 0 means no program. The outcome variable, the added installation capacity at region i and time t is denoted as y_{it}. To better illustrate the impact of potential confounders, I use X_{it} to denote a set of exogenous covariates and Z_{it} a set of confounders. $\tilde{X}_{it}$ and $\tilde{Z}_{it}$ denote their their history up to time t.

Two assumptions are needed to identify the causal impact of the treatment: the unconfoundedness assumption (Rosenbaum and Rubin, 1983, 1985) and selection-on-observable assumption (Barnow et al., 1980). The former is mathematically expressed as

$$y_{it}^{0}, y_{it}^{1} \perp R_{it} | \tilde{Z}_{it}, \tilde{X}_{it}, \tag{19}$$

for all i and t, and y_{it}^{0} and y_{it}^{1} are counterfactuals of y that would have been observed under $R_{it} = 0$ and $R_{it} = 1$ respectively. This means that conditional on the history of confounding and exogenous covariates, potential outcomes are independent from treatment status. Propensity score, which measures the probability of selection intro treatment, reduces the dimensions of matching covariates, and assumption (19) can be written as

$$y_{it}^{0}, y_{it}^{1} \perp R_{it} | p(\tilde{Z}_{it}, \tilde{X}_{it}), \tag{20}$$

where $p(\tilde{Z}_{it}, \tilde{X}_{it}) = Pr(R_{it} = 1 | \tilde{Z}_{it}, \tilde{X}_{it})$. The above assumption implies that propensity score can remove all the bias associated with the differences in covariates.

Under unconfoundedness assumption, Hirano, Imbens and Ridder (2003) show that the difference between the average outcome of the treatment and control observations, weighted by the inverse propensity score, is an efficient estimator of the average treatment effect for the treated. The estimated treatment effect is

$$\hat{\tau} = \frac{\sum_t \sum_i y_{it} \cdot R_{it}}{\sum_t \sum_i R_{it}} - \frac{\sum_t \sum_i y_{it} \cdot \hat{p}(\tilde{Z}_{it}, \tilde{X}_{it}) \cdot (1 - R_{it})/(1 - \hat{p}(\tilde{Z}_{it}, \tilde{X}_{it}))}{\sum_t \sum_i \hat{p}(\tilde{Z}_{it}, \tilde{X}_{it}) \cdot (1 - R_{it})/(1 - \hat{p}(\tilde{Z}_{it}, \tilde{X}_{it}))}, \tag{21}$$

where $\hat{p}(\tilde{Z}_{it}, \tilde{X}_{it})$ is the estimated propensity score based on the observed covariates. The first term of equation (21) is the weighted sample average outcome of the treatment group, and the second term is the weighted sample average outcome of the control group.

The other assumption for causal identification is selection on observables, which states that selection into treatment is solely based on observed factors in the data. This assumption is untestable and can be considered to be fairly strong. I provide several reasons below to justify the use of IPTW for causal identification despite such strong assumption. According to Azoulay et al. (2009), methods that assume selection on observables typically perform well compared to experimental benchmarks if (1) a rich set of covariates is used to model the treatment selection process; (2) observations are drawn from similar markets; (3) outcomes in treatment and control groups are measured in the same way. According to section 4, condition (2) and (3) can be satisfied here. Regarding condition (1), one might wonder to what extent the factors determining the creation of a solar rebate program are accounted for. As shown in section 4, I include as many variables as I can to reflect the factors that can potentially influence or are associated with the establishment of rebate programs, including variables on natural resource endowment, political climate, solar related policies and legislation, and demographic factors.

Despite my best effort to include as many measures and proxies of the determinants of program selection, it is unlikely that the list of covariates is exhaustive. For example, I do not observe environmental awareness of residents, which might be different from the politicians representing them.

In addition to unobserved factors determining selection of treatment and outcome, there are two more potential sources of statistical endogeneity: reverse causality and measurement error. It is possible that state governments or utilities see declining or stagnant residential solar installations, and decide to create solar rebate programs to promote more installations. However, outcome is unlikely to influence the treatment status in the same time period. Furthermore, agencies that reported their solar installation data to be part of the Open PV data set are likely to be different from the ones that did not report their data. Hence, the causal estimation presented replies on the *reported* solar installation information.

5.2 Propensity score estimation

Commonly in literature, researchers use parametric methods, such as logit and probit regressions, to estimate propensity scores for binary treatments (Austin, 2011; Watkins et al., 2013). However, there is lack of consensus in the applied literature on how to define model specification, including functional form and variable selection (Austin, 2011). Misspecification of the propensity score model, especially omitting confounders, can lead to biased estimates (Drake, 1993).

In recent years, evidence has shown that machine learning methods perform better than simple logit regressions in terms of bias reduction and mean squared errors, especially in the presence of nonlinearity and nonadditivity (Watkins et al., 2013; Lee et al., 2010; Harder et al., 2010). One of the machine learning methods that are commonly used to estimate propensity scores for binary treatment is Generalized Boosted Model (GBM).

GBM fits a sequence of regression trees $\{G_1, G_2, ..., G_m, ..., G_M\}$ to one training data sample, and combines these weak models into an ensemble of powerful "committee" with greatly improved performance compared to individual regression trees (Friedman et al., 2001). Each observation has a weight, and initially all observations are equally weighted. In iteration m, more weights are added to the observations that were misclassified by the previous model G_{m-1}while less weights are given to the ones that were classified correctly. As iterations proceed, the algorithm focuses more on the training observations that are hard to classify. GBM computes a weight α_m for each tree G_m based on their classification accuracy. The final output is the weighted average of the regression trees from all iterations

$$G = \sum_{m=1}^{M} \alpha_m G_m.$$

This flexible estimation method can accommodate a large set of covariates, and capture complex and nonlinear relationships between the treatment and covariates without over-fitting the data (McCaffrey et al., 2004). In addition, the "twang" package in R statistical software, which implements GBM, can run multiple iterations to find the propensity score model that generates the best balance in covariates between treatment and control groups (Ridgeway et al., 2006). Moreover, GBM ranks the relative power of covariates in predicting treatment status, which provides empirical insights on the determinants of solar rebate program creation.

6 Results

In this section, I first present the balance tests used to assess the difference in weighted covariates between the treated and untreated observations, and show that GBM performs better than logit regression. Using the estimated propensity scores, I present the estimation results using causal forests and analyze the distribution of treatment effects. The current estimation uses contemporaneous covariates for propensity score estimation and causal forests. Robustness checks using linear regression methods and demeaned outcomes are in the end.

6.1 Balance diagnostics

Propensity scores are estimated using GBM and contemporaneous covariates that are not affected by the rebate programs. Assessing whether the propensity scores balance the characteristics of treatment and control group is critical in satisfying the unconfoundedness assumption. Unbalanced covariates are likely to predict treatment selection, and nonoverlapping distributions of propensity score between treatment and control group suggest one or more covariates are predictive of treatment selection (Curtis et al., 2007). Figure 7 shows there is substantial overlap in distribution of the propensity score between the treatment and control group.

Another common indicator used to assess post-weighting balance is effective size (or absolute standardized bias), which equals the absolute difference in weighted means between the treatment and control observations divided by standard deviation (Harder et al., 2010; McCaffrey et al., 2013; Watkins et al., 2013). The expression of effective size for covariate k is

$$SB_k = \frac{\mid \bar{X}_{k,R=1} - \bar{X}_{k,R=0} \mid}{\sqrt{\frac{1}{2}\delta^2_{k,R=1} + \frac{1}{2}\delta^2_{k,R=0}}}, \tag{22}$$

where $\bar{X}_{k,R}$ is the weighted mean of covariate k for treatment $(R = 1)$ and control $(R = 0)$, and $\delta_{k,R}$ is the covariate k's standard deviation in the treatment $(R = 1)$ and control $(R = 0)$ group. Standardized bias provides a convenient way to assess the balancing property across all covariates and allow the

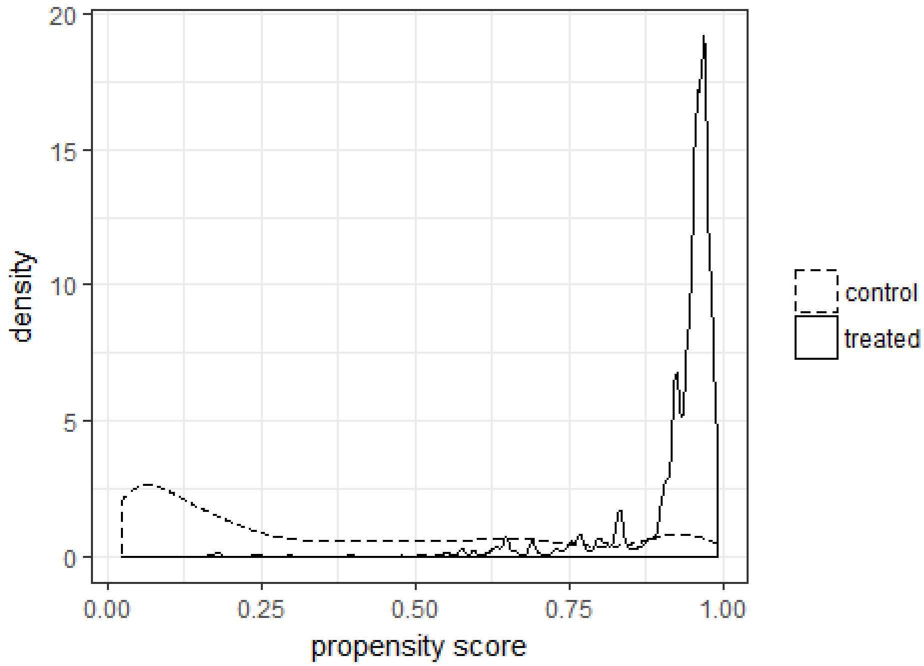


Figure 7: Distributions of propensity score in treatment and control group

ranking of covariates by the amount of unbalance (McCaffrey et al., 2013). Although there is no standard criterion, researchers often consider an effective size of 0.25 to be a good cutoff for a balanced covariate (Rubin, 2001; Harder et al., 2010). Some researchers adopt a 0.2 cutoff and consider any effective size greater than 0.2 to be problematic (McCaffrey et al., 2013).

According to McCaffrey et al. (2013), the key to use GBM for propensity score estimation is to find the optimal iteration (i.e. number of "trees") that minimizes a "stopping rule" based on the difference in weighted distribution of covariates between the treated and control groups, such as effective size. In this analysis, I use the average effective size across covariates to identify the optimal iteration. Interaction depth, which controls the maximum level of interactions allowed in the model, is set at 2. This means only interaction between two covariates (same or different) are allowed in the model. A shrinkage parameter of 0.01, commonly adopted in literature, is applied to enhance the smoothness of the resulting model. The optimal number of iterations that corresponds to the minimum average effective size is 1814.

Table 17 compares the effective size for each covariate in the unweighted sample, sample weighted using the GBM propensity score and sample weighted using the logit propensity score. In the unweighted sample, the effective size of some variables, such as solar insolation, cost of solar

Table 17: Comparison of effective size of covariates

	Unweighted	GBM weighted	Logit weighted
Interconnection score	0.104	0.120	0.002
Net metering score	0.186	0.040	0.753*
Have SREC or production tax credit program	0.377*	0.169	0.705*
Deregulated utilities	0.247*	0.026	0.333*
Solar rights regulation	0.521*	0.229*	1.395*
Third party ownership allowed	0.109	0.036	5.488*
Number of customers in green pricing program	0.155	0.012	0.429*
Community solar garden capacity (kW)	0.079	0.044	0.438*
Average annual solar insolation (kWh/m2/day)	0.212*	0.019	0.385*
Cost of solar installation ($/W)	0.506*	0.123	0.305*
Residential electricity rate (cents/kWh)	0.270*	0.035	1.615*
Housing density	0.002	0.076	20.837*
Population density	0.008	0.083	20.648*
Median house value	0.074	0.030	0.926*
Median income ($/year)	0.018	0.057	3.266*
Bachelor degree or higher (%)	0.246*	0.002	2.812*
Average household size	0.180	0.045	0.756*
GDP from mining industry (%)	0.038	0.034	0.035
Have RPS	0.126	0.023	0.094
RPS % (if RPS=1)	0.026	0.037	1.714*
RPS ending year (if RPS=1)	0.129	0.025	0.107
RPS establishing year (if RPS=1)	0.138	0.033	0.119
RPS has solar carve out (SCO)	0.598*	0.118	0.761*
Solar carve out % (if SCO=1)	0.841*	0.153	0.445*
Solar carve out ending year (if SCO=1)	0.601*	0.118	0.761*
Senate environmental voting score	0.026	0.074	0.357*
House environmental voting score	0.383*	0.043	0.826*
Wind energy potential (MW)	0.077	0.004	0.197
Year of installation	0.670*	0.114	0.889*

Cells marked with an * indicate effective size greater than 0.2.

installation and the house environmental voting score, are greater than 0.2. After weighted by the GBM propensity scores, all the covariates, except for the dummy variable on solar rights regulation, are balanced with the effective size under 0.2. The effective size of this variable is still under 0.25, which are within the threshold for unbalanced covariates used by Rubin (2001) and Harder et al. (2010). I then compare the post-weighting balancing results using logit estimated propensity scores. Many of the covariates are unbalanced, even more than the unweighted sample. This demonstrates that GBM can generate better balanced outcome without pre-specify functional form.

Another way to examine the balancing property of post-weighting sample is the comparison of variable distribution. Graphic presentation of the empirical probability distribution functions (PDFs) offers a descriptive and broad comparison of a continuous variable between two groups in the sample (Austin and Stuart, 2015). One can assess whether the distribution of the variable differs by treatment and control groups. Figure 8 presents the PDF comparison of three continuous covariates in the post-weighting sample. We can see that before weighted by the inverse propensity score weights, distribution of these variables are quite different: the value of solar insolation in the control group is more concentrated between 4.5 and 5 kWh/m^2/day. After weighting, the distribution between treated and control becomes much more similar, although not completely identical. To make the comparison more rigorous, I use Kolmogorov–Smirnov (KS) test to examine whether the distributions in treated and control groups differ. The test statistic is defined as the maximum vertical distance between the two empirical cumulative distribution functions (CDFs) of the variable in two groups (Austin and Stuart, 2015). Table 18 shows the KS test statistic of all the covariates used for propensity score estimation. As the KS test measures the distance between two distribution, the closer to zero the test statistic, the less difference between the distribution. Before weighting, the KS statistic ranges from 0.011 (have RPS) to 0.356 (solar carve out ending year), and the average is 0.184. After weighting, the KS statistic ranges from 0.002 (have RPS) to 0.147 (RPS establishing year), and the average is reduced to 0.062. The test statistic is lower for every variable after weighting compared to it before weighting.

Table 18: Comparison of Kolmogorov-Smirnov test statistics of covariates

	Unweighted	GBM weighted
Interconnection score	0.076	0.044
Net metering score	0.064	0.031
Have SREC or production tax credit program	0.179	0.081
Deregulated utilities	0.077	0.008
Solar rights regulation	0.255	0.110
Third party ownership allowed	0.018	0.006
Number of customers in green pricing program	0.278	0.057
Community solar garden capacity (kW)	0.210	0.035
Average annual solar insolation (kWh/m2/day)	0.135	0.041
Cost of solar installation ($/W)	0.232	0.079
Residential electricity rate (cents/kWh)	0.222	0.095
Housing density	0.110	0.046
Population density	0.078	0.045
Median house value	0.099	0.057
Median income ($/year)	0.071	0.049
Bachelor degree or higher (%)	0.134	0.037
Average household size	0.112	0.049
GDP from mining industry (%)	0.281	0.076
Have RPS	0.011	0.002
RPS % (if RPS=1)	0.244	0.065
RPS ending year (if RPS=1)	0.218	0.142
RPS establishing year (if RPS=1)	0.212	0.147
RPS has solar carve out (SCO)	0.273	0.055
Solar carve out % (if SCO=1)	0.291	0.071
Solar carve out ending year (if SCO=1)	0.356	0.089
Senate environmental voting score	0.233	0.055
House environmental voting score	0.327	0.082
Wind energy potential (MW)	0.266	0.097
Year of installation	0.279	0.052

It is common in literature to assess the balancing property of estimated propensity scores using hypothesis tests, especially using t-tests and their p-values (Rosenbaum and Rubin, 1984; Imai,

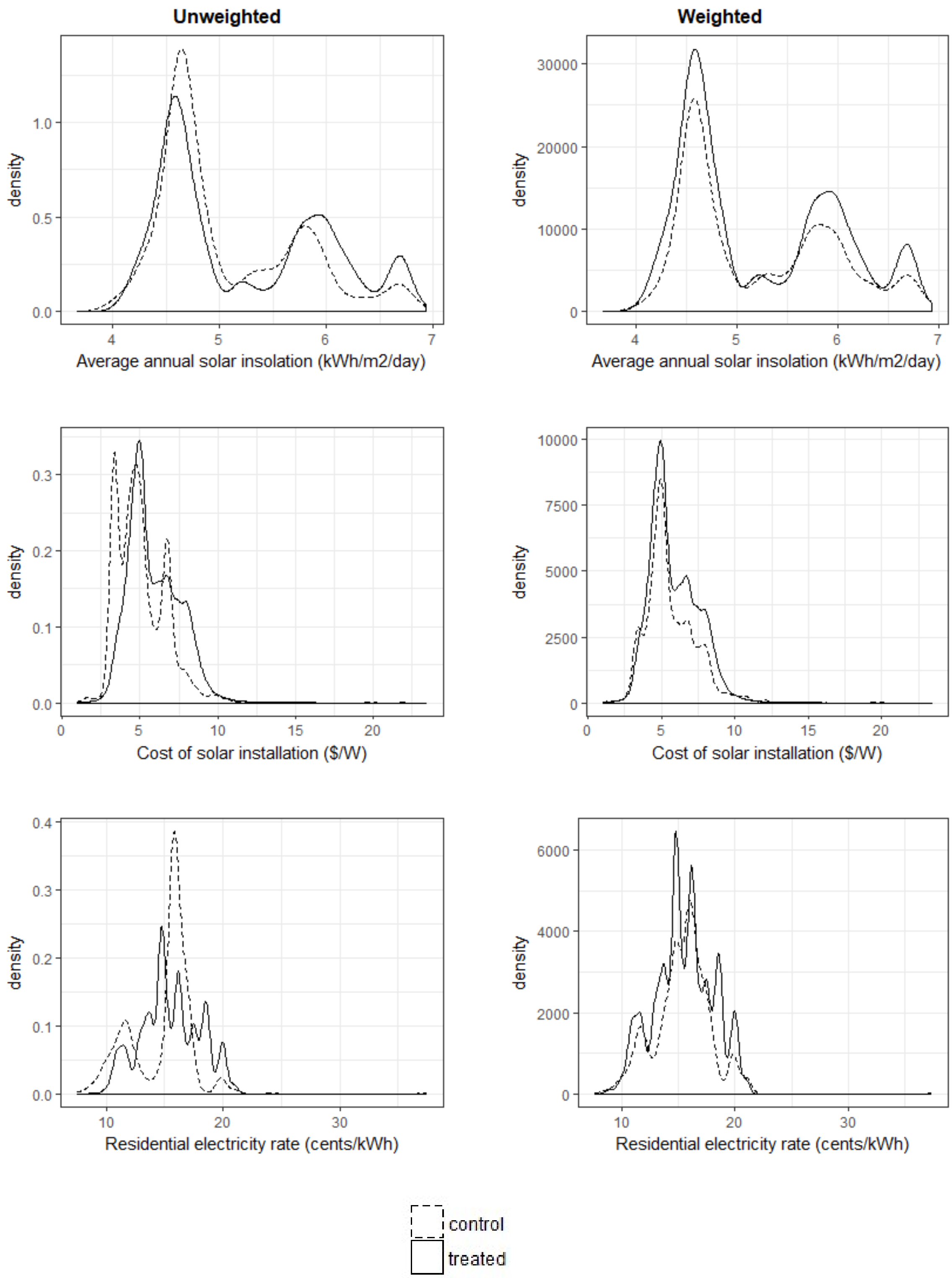


Figure 8: Distribution of three continuous variables between treated and control groups

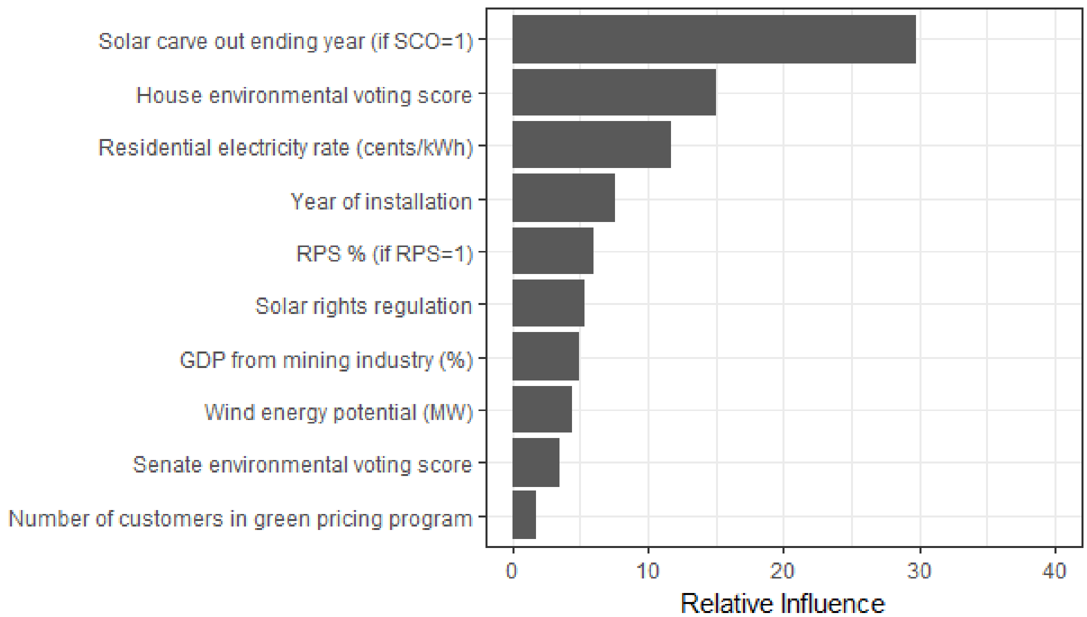


Figure 9: Relative influence at predicting treatment (top 10 covariates)

2005). Statistically insignificant t-tests are interpreted as satisfying balancing requirements for causal inference. Imai et al. (2008) showed such approach can be problematic. First, randomly dropping control observations can reduce t-statistics to 0, falsely indicating improvement in balance while the true balance does not change systematically. More observations that are dropped, the less power t-tests have to detect imbalance in covariates. Second, we are interested in assessing the balance of the sample, instead of the hypothetical population from which the sample is drawn. Due to these reasons, the balancing tests in this paper focus on effective size and distribution comparison of the sample data.

Another advantage of using GBM to estimate propensity score is that it gives the ranking of relative influence of covariates at predicting the probability of receiving the treatment. GBM generates relative importance of predictors based on the number of times a variable is selected for splitting, weighted by the squared improvements and averaged across all the trees (Friedman and Meulman, 2003). The ending year of the solar carve out requirement has the highest predictive power, followed by the political indicator, house environmental voting score. Variables, such as past year added installation capacity, percentage of people with bachelor or higher degree and average household size, do not have much explanatory power for establishing rebate programs.

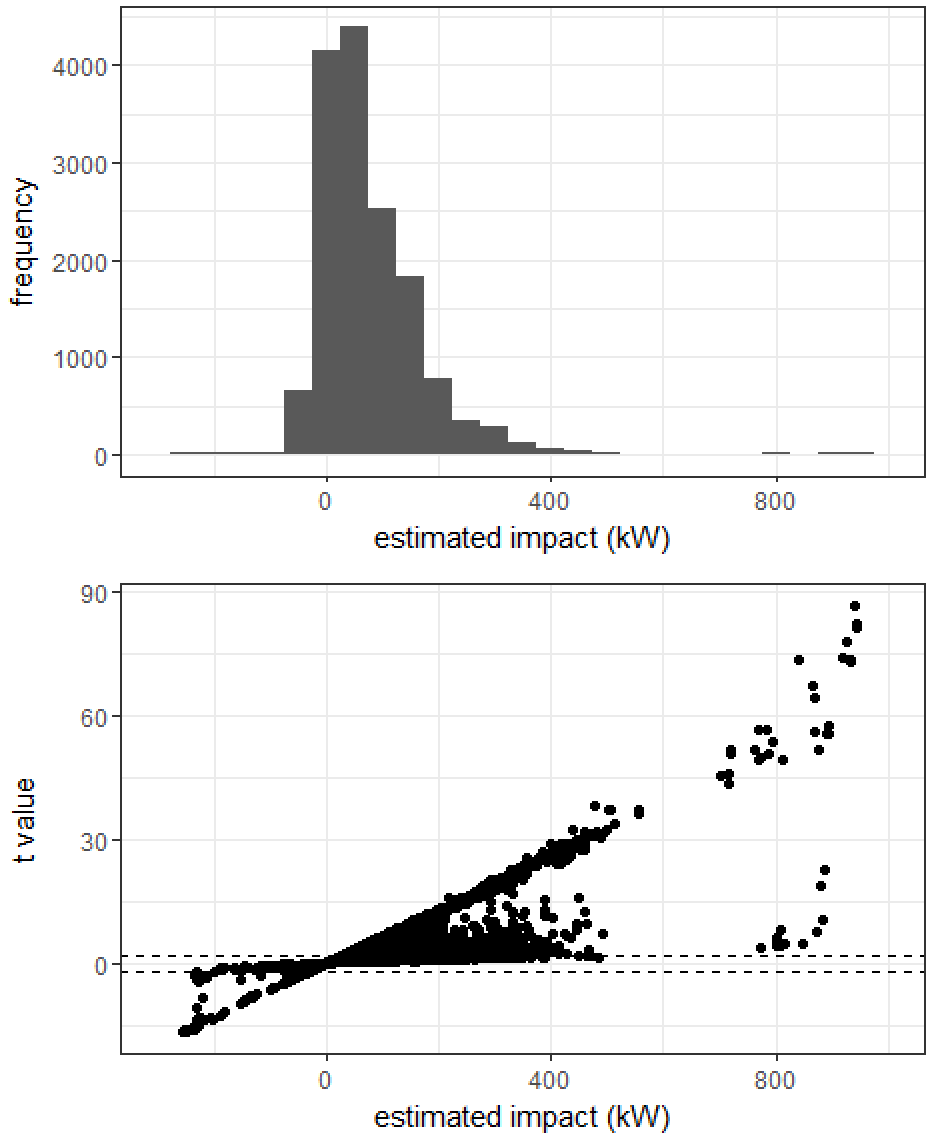
6.2 Causal regression forest

A treatment effect is estimated for each observation by building a causal forest with 1000 trees. Half of the sample is used to build causal forest (i.e. the training sample) and the other half is used to estimate treatment effect (i.e. the estimation sample). A bootstrapped sample, which half of the training sample, is randomly drawn without replacement to build each tree in the forest. The minimum number of observations in a leaf is set to be 10. In addition to the variables used to estimate propensity scores, three additional covariates are added: rebate level per watt, maximum rebate in the zip code region and added installation capacity in previous year. There are 32 covariates in total and 20 of them are randomly selected in each iteration to build a tree, which avoids repeatedly splitting on one variable (Wager and Athey, 2017).

6.2.1 Distribution of treatment effects

Figure 10 shows the distribution of treatment effects and their t-values (dashed lines are 1.96 and -1.96, respectively, corresponding to p value of 5%). The average treatment effect is 76.06 kW, which means on average additional 76.06 kW of residential solar capacity is installed in a zip code region in a year that has a rebate program compared to the ones without rebate programs. The highest treatment effect of 944.93 kW and the lowest treatment effect of -254.35 kW, and the majority of the effects are positive. About 44.29% of the observations have statistically insignificant impact with t value between -1.96 and 1.96. Only 2.08% of the individual treatment impacts are negative and statistically significant at 5% level (t value < -1.96), while 53.62% of the observations have statistically significant and positive treatment impacts.

To summarize the treatment effect distribution and visualize the interrelationships of variables, a regression tree is built to predict the estimated treatment effects in the estimation sample. Recall that causal forest creates a function $F(X)$ that estimates treatment effect for each observation (i.e. $\tau(X_i) = F(X_i)$). The causal forest is "honest" because it uses part of the sample to generate the function, and the other part to estimate treatment effects. The following regression tree is built on the estimation sample by predicting the treatment effects estimated by the causal forest. The goal is to summarize the estimated treatment effects and identify the main channels which lead to heterogeneity. Cross validation is used to pick the best tree structure corresponding to the minimum



Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
-254.35 kW	16.78 kW	53.24 kW	76.06 kW	117.68 kW	944.93 kW

Figure 10: Distribution of treatment effects from causal forest

out-of-sample prediction error.

The tree shown in Figure 11 depicts the relationship between the policy and non-policy variables in predicting treatment effects of rebate programs. The left branches are conditional on the nodes being true, while the right branches are conditional on the nodes being false. Ending leaves represent the subgroups of the partition where the observations within leaves have relatively homogeneous treatment effects, while the observations across leaves have more distinct treatment effects. Average treatment effects and numbers of observations of each node are also presented.

Overall, the left part of the tree conditioning on the RPS percentage lower than 29.5% has smaller average treatment effect than that of the right part of the tree if the RPS percentage higher than or equal to 29.5%. The ending leaf with the highest average treatment effect (854) only has 32 observations. These observations have higher RPS percentage, higher past year added capacity, lower cost of solar installation and median house value between 484,500 and 497,000. The lowest average treatment effect in an ending leaf is -147.6 with 114 number of observations. These observations have installations more recently and their RPS percentage lower than 29.5%. Their current community solar capacity is higher than 10330 kW and have electricity rate lower than 18.71 cents/kWh. The structure of the regression tree indicates the distribution pattern of treatment effects, and can be used to target program recipients and locations for program implementation.

In regression trees, variable importance measures the improvement in goodness of fit when a covariate is used to split the sample (Friedman et al., 2001). Variable importance ranking provides insights on the factors that play significant roles in explaining varying treatment effects of rebate programs. Only 11 out of 32 variables are used to split the tree, and Figure 12 shows the ranking of the variable importance. RPS percentage plays the most significant role in explaining the variation of treatment effects of rebate programs, followed by residential electricity rate, year of installation, median house value in the county and past year added capacity. RPS percentage indicates the goal of renewable energy integration set by state government, and higher percentage suggests better legislative support to renewable energy development. High residential electricity rate indicates high incentive for households to generate electricity themselves. Cost of solar installation, together with electricity rate, determine the profitability of net-metered electricity. Year of installation reflects the general time trend of technology adoption as well as changes in federal policies, while past year added capacity reflects peer effect of adopting new technologies and the "learning by doing"

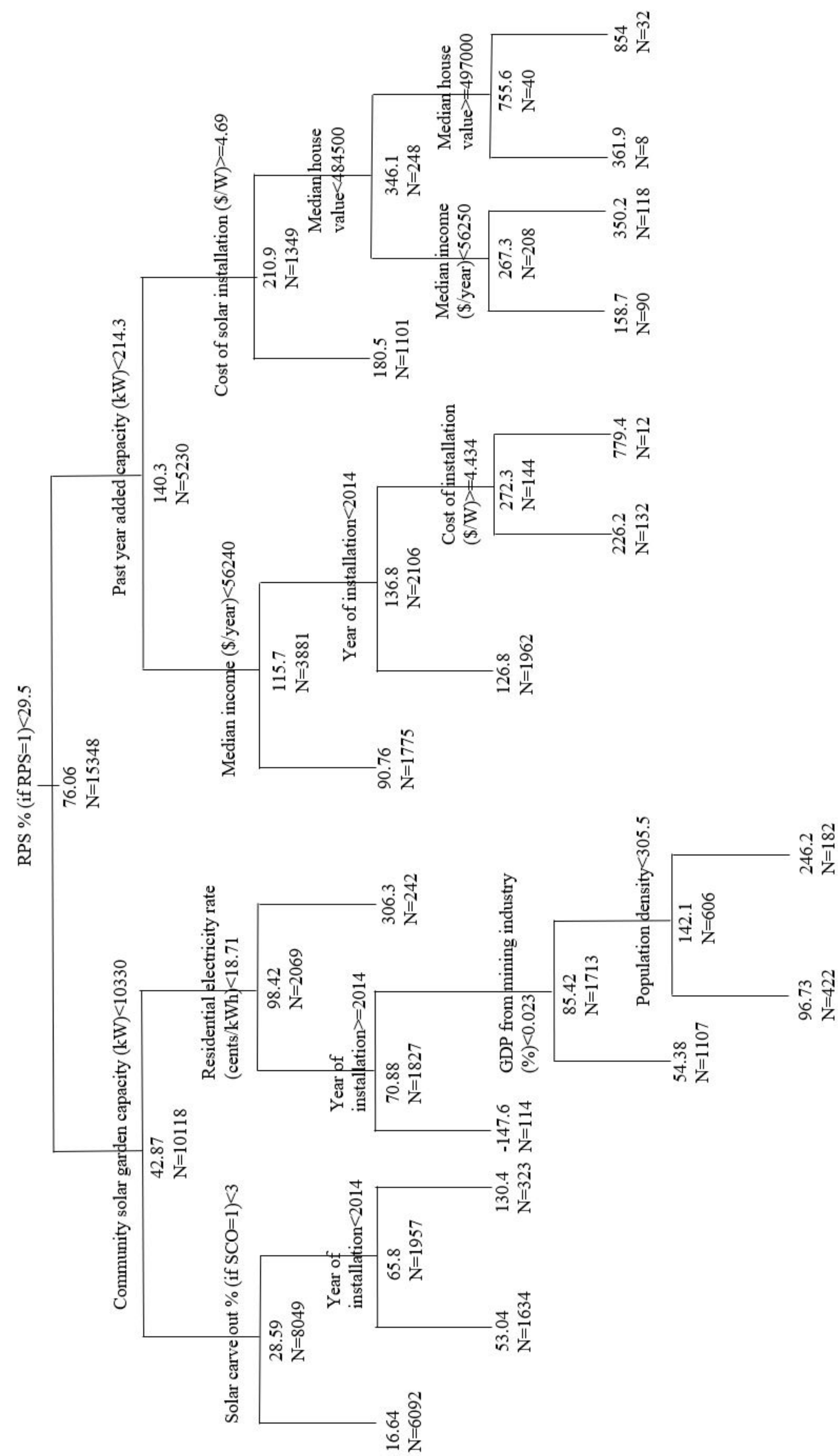


Figure 11: Regression tree of estimated treatment effects (kW)

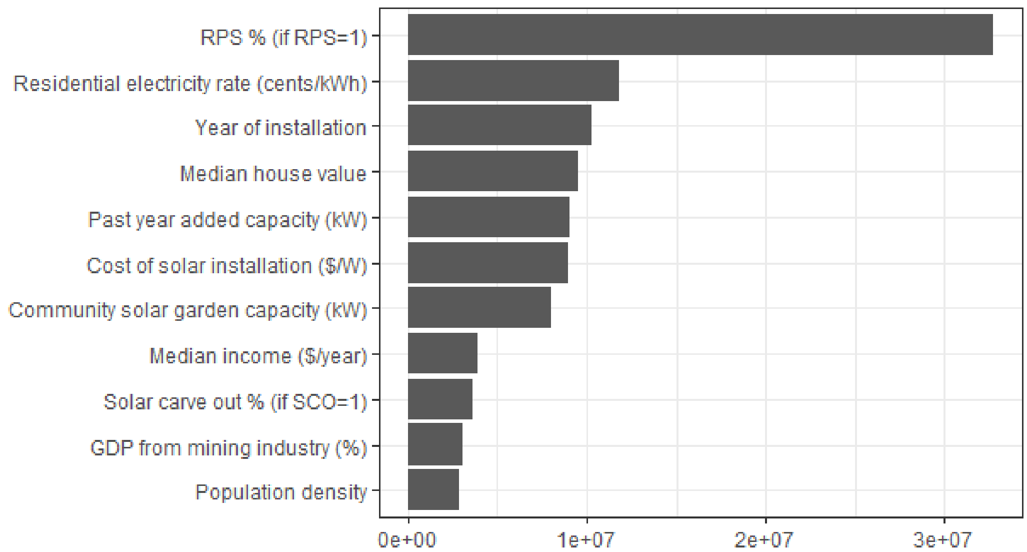


Figure 12: Variable importance ranking in explaining treatment effect heterogeneity

effect. Community solar garden capacity in 2016 reflects the availability of alternative options to "go solar", which also measures households' attitude towards solar energy. Demographic variables, such as median house value, median income and population density, also play important roles in explaining the variation.

6.2.2 Partial dependence relationships

In addition to examining the structure of the regression tree on estimated treatment effects, it is also useful to see how their value changes with the value of some variables of policy interest. Next I present partial dependence plots (Figure 13) that depict relationships between treatment effects and some variables of interest, including residential electricity rate, median house value, past year installation level, cost of installation, median income and population density. Each point represents one observation in the estimation sample. These partial relationships are derived by changing the value of the variable of interest, while holding all other covariates constant at their sample means.

These relationships display significant nonlinearity. In Figure 13, plot A shows a generally positive correlation between treatment effects of rebate programs and residential electricity rate. Treatment effects seem to decline slightly when electricity price is between 11 cents/kWh and 12 cents/kWh, but increases with price if its value is between 12 cents/khW and 16 cents/kWh. Plot B shows an inverted U shaped relationship between the treatment effect and median house value, with the treatment effect peaking around \$375,000. Plot C shows that past year added capacity is positively associated with the treatment effect when the added capacity is between 1200 kW and 1500 kW, but the positive correlation disappears if the added capacity is greater than 1500 kW. Regarding the cost of solar installation in plot D, the treatment effect seems to go up when cost of installation increases from \$4/W to \$5/W, and peaks at \$5/W, then declines as cost continues to increase and stays constant after cost reaches \$8/W. There is a positive correlation between treatment effect and median income when median income is between \$50,000 and \$62,500, and the positive relationship dissipates after median income gets higher than \$62,500. At last, the association between treatment effect and population density is first positive and then negative, peaking around 625 per square mile. If population density is higher than 1800 per square mile, the correlation becomes zero.

6.3 Robustness checks

In this section, I test whether the estimated treatment effect and its distribution are robust to other empirical model specifications. To control for the time-invariant and region-invariant unobserved factors, I build causal forests on the demeaned outcomes to see whether treatment effect distribution is different from the main model. In addition, traditional econometric methods, including unweighted and weighted Ordinary Least Squares (OLS), fixed effect and random effect models, are used to estimate average treatment effect and compared with the results from causal forests.

In a panel data setting, fixed effect models are often used to control for unobserved factors that are time-invariant but heterogeneous across units (e.g. regional or individual fixed effect) or common time trend for all units (e.g. year fixed effect). The outcome is assumed to be linear function of these unobserved factors, hence subtracting the group level or year level mean from the values of outcome eliminates the unobserved factors, yielding unbiased estimates of the coefficients of interest. Adopting the assumption that unobserved heterogeneity is linear to outcome, I build causal forests on demeaned outcomes to see whether the treatment effect distribution change significantly after removing certain unobserved heterogeneity[14]. Specifically, the outcome is demeaned at the state level and at the year level. The former is aimed to eliminate state level unobserved factors,

[14] Unlike linear fixed effect model, covariates are not demeaned because they are only used to split trees. The formula used to calculate treatment effect using demeaned outcome is the same as equation 21, but it replaces y_{it} with $\ddot{y_{it}} = y_{it} - \bar{y}_i(\bar{y}_t)$.

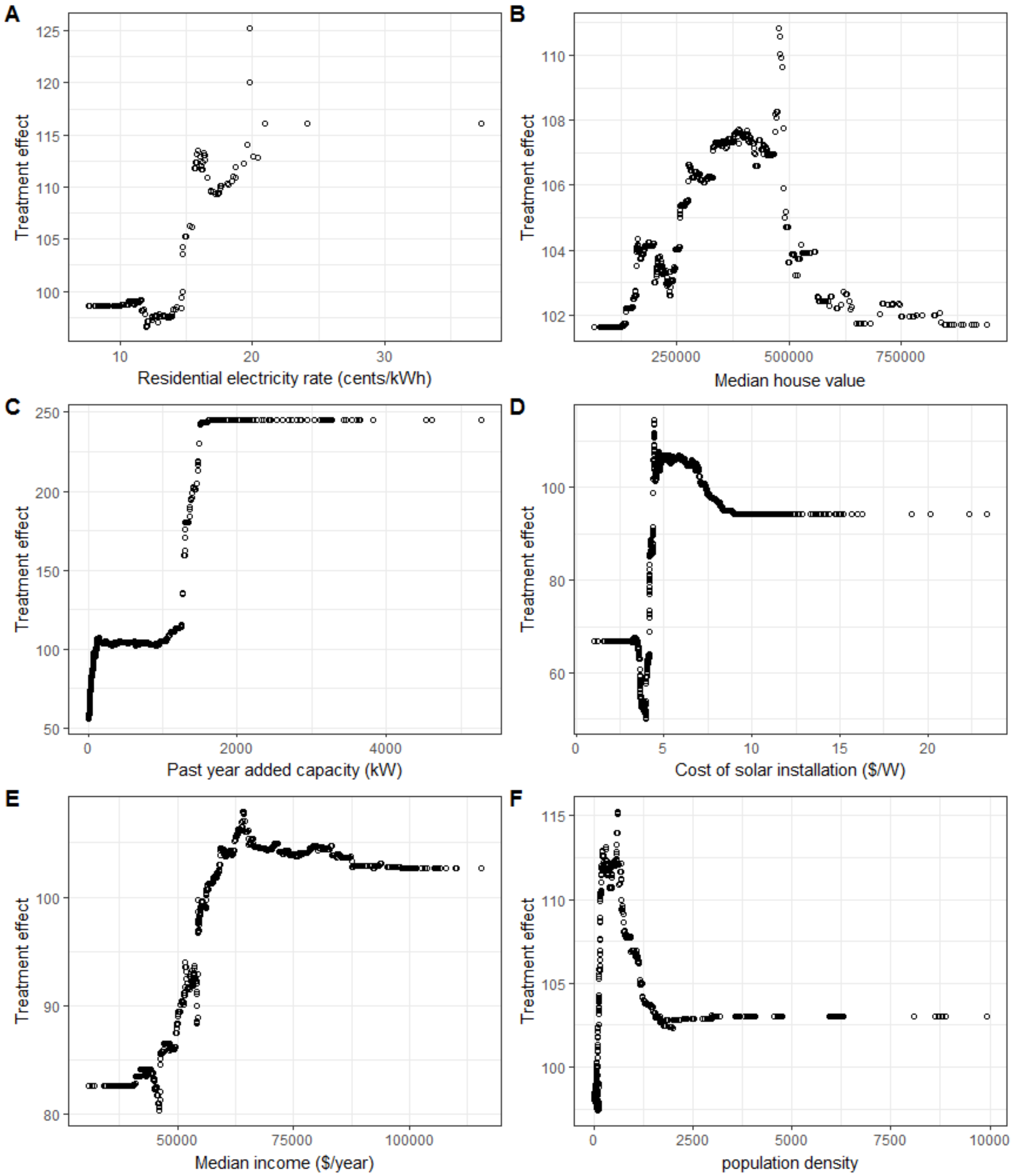


Figure 13: Partial dependence plots

such as unmeasured political factors and public attitude towards renewable energy and unmeasured state level policies; the later is aimed to eliminate common time trend shared by all observations, such as federal level solar policies and general solar market shocks. Table 19 shows the distribution of estimated treatment effects and their t-values. We can see that the treatment effects estimated using the demeaned outcomes are slightly higher than the ones using the original outcome, with about 21% and 25% increase in median value, as well as 18% and 29% increase in average value, for the state level and year level demeaned outcome respectively. The standard deviation of treatment effect distribution is similar between the case with original outcome and the case with state level demeaned outcome, but the case with year level demeaned outcome has slightly higher standard deviation. The distribution of t values are very similar. Overall, the distribution of treatment effects are robust when the outcome is changed to demeaned outcomes at state and year level.

Table 19: Comparison of treatment effect distribution between original and demeaned outcomes

Panel A: Original Outcome							
	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	S.D.
$\hat{\tau}$	-254.35	16.78	53.24	76.06	117.68	944.93	94.74
t value	-16.70	0.79	2.18	3.33	4.70	86.40	4.88

Panel B: State level demeaned outcome							
	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	S.D.
$\hat{\tau}$	-213.74	38.69	64.81	90.39	114.12	852.19	96.26
t value	-14.26	1.76	3.14	4.12	5.06	79.05	4.97

Panel C: Year level demeaned outcome							
	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	S.D.
$\hat{\tau}$	-272.21	30.98	66.96	98.66	148.39	1006.13	115.52
t value	-14.94	1.27	2.63	4.05	5.78	58.97	5.06

Finally, I run multiple linear models to see whether the statistically significant average treatment effects persist in linear specifications. Specifically, six linear models are presented Table 20: (1) unweighted OLS with full set of controls; (2) IPT weighted OLS with the three additional covariates not used in propensity score estimation (i.e. rebate level, maximum rebate level, past year added capacity); (3) IPT weighted OLS with full controls; (4) state level fixed effect; (5) year level fixed effect; and (6) zip code level random effect. Zip code level random effect model instead of zip code level fixed effect model is used so that the degree of freedom is not reduced significantly. The estimated coefficient of the treatment variable, have solar rebate program, is statistically significant across all six specifications, and the size of the estimated coefficient is also quite stable, except for in the state fixed effect model. The size of estimated treatment effects from the linear models are not technically comparable with the IPTW estimator used in causal forests because of different underlying assumptions. In particular, the interactions and nonlinearities that the causal forests approach uncovered violates the assumptions of conventional OLS approach. The estimated coefficients of the three additional covariates are also in Table 20. The effect of rebate level per watt on outcome has mixed estimates, while maximum rebate level and previous year added capacity are statistically significant and positive.

Table 20: Linear model estimation results

	(1) OLS 1	(2) OLS 2	(3) OLS 3	(4) State FE	(5) Year FE	(6) Zip code RE
Have solar rebate program	11.58***	13.15***	11.35***	35.81***	17.759***	11.58***
	(3.75)	(3.60)	(4.17)	(5.02)	(4.11)	(4.11)
Rebate level ($/W)	3.06**	-9.57***	0.87	-1.51	-4.86***	3.06**
	(1.27)	(1.17)	(1.37)	(1.57)	(1.53)	(1.49)
Maximum rebate level ($)	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Past year added capacity (kW)	1.18***	1.23***	1.20***	1.17***	1.18***	1.18***
	(0.02)	(0.02)	(0.02)	(0.00)	(0.00)	(0.00)
Observations	30,696	30,696	30,696	30,696	30,696	30,696
Full controls	Yes	No	Yes	Yes	Yes	Yes
IPT weights	No	Yes	Yes	No	No	No

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

7 Conclusion and discussion

Previous literature has evaluated the impacts of regulatory policies (e.g. RPS, interconnection and net metering standards) and financial incentives (e.g. rebates, renewable energy credits) on residential solar energy adoption in various settings (Carley, 2009; Crago and Chernyakhovskiy, 2017; Hughes and Podolefsky, 2015; Krasko and Doris, 2013; Sarzynski et al., 2012). Building upon the previous work, this paper asks more nuanced questions: "Does an incentive program with positive average treatment impact benefit everyone?" and "Under what conditions does a program generate substantial impacts?". The empirical results using IPTW method and causal forests show that solar rebate programs are on average effective at promoting residential solar installations, but the treatment effect varies greatly. The analysis identifies factors that are important in explaining treatment effect variation. Policy related factors are RPS percentage and solar carve out percentage. Important market characteristics are residential electricity rate, past year added capacity, cost of solar installation and community solar garden capacity. Demographic factors playing important roles are county level median house value, county level median income and population density. Other important factors include year of installation and percentage of GDP from mining industry. On the other hand, factors that do not explain much of the treatment effect variation include rebate level, interconnection and net metering standards and other financial incentives. Education level and household size do not seem to play important roles either. In addition, relationships between treatment effect and important explanatory factors are nuanced and display significant non-linearity. Several policy implications can be drawn from the empirical results.

First, legislative goals matter. The regression tree in Figure 11 shows that the average treatment effects differ between the group with RPS mandate higher than 29.5% and the one with lower than 29.5%. Specifically, regions with RPS mandate higher than 29.5% have an average treatment effect of 140.3 kW, over three times higher than these with RPS mandate lower than 29.5%. Similarly, regions with higher than 3% solar carve-out mandate have about three times higher average treatment effect than those with lower than 3% solar carve out mandate, given these regions have lower than 29.5% RPS mandate and less than 10330 kW community solar garden capacity in 2018. These associations, if reflecting the underlying causal mechanism, suggest that legislative goals set by state governments regarding renewable energy or solar energy can be important at promoting rebate program effectiveness as they raise public awareness about this new technology, reduce investment uncertainty and create friendly market environment for solar developers. In addition, rebate programs are likely to be rolled out under the guidance of RPS policies, so states with high RPS mandates are likely to have better rebate program design, such as ease to claim (Sarzynski et al., 2012), and load-serving entities in these states face stronger incentives to distribute rebates to meet their RPS requirements.

Second, certain solar market characteristics are associated with high rebate program effects. Overall, regions with high treatment effect of rebate programs also have high residential electricity rate and high cost of solar installation. Studies have found that consumers are more likely to install PV facing higher electricity prices (Sarzynski et al., 2012) and lower installation costs (Bollinger and Gillingham, 2012b). Given this evidence, it is not surprising that rebate programs can induce higher PV adoption where people seek alternative energy sources to reduce expenditure on electricity and face higher upfront investment costs. Past year added installation reflects the maturity of local solar markets and peer effects. In regions with more well established solar developers and households with PV installations, the process of obtaining rebates is likely to be easier and more streamlined, and more people are aware of the benefits of rebate programs. On the other hand, as shown in Figure 13, peer effect can only promote rebate program effectiveness to a certain degree. If past year added capacity exceeds 1800 kW, additional lagged installation is not associated with a higher treatment effect. Community solar gardens, an alternative to rooftop solar, also predict treatment effect variation. Among the observations with RPS mandate lower than 29.5%, those in states with community solar garden capacity higher than 10 MW in 2018 have an average rebate effect about 2.4 times higher than the rest. This suggests that people in states with higher community solar garden capacity also receive greater benefits from rebate programs.

Third, supporting and competing policies have little effect on rebate program impacts. Based on the framework for policy stacking Krasko and Doris (2013), financial incentives are third tier policies built upon market preparation policies (e.g. interconnection and net metering standards) and market creation policies (e.g. RPS). Hence, the quality of interconnection and net metering standards are likely to influence the effectiveness of rebate programs. However, empirical evidence in this paper does not support this hypothesis. This is likely due to the fact that during the study period (2008-2015), interconnection and net metering standards in these states have been well established to accommodate residential solar installations. The variations in "Free the Grid" scores assessing these two policies more likely reflect regulation on large scale solar installations. Solar rights regulation and green pricing programs are important predictive variables on the existence of rebate programs, but do not explain the treatment variation. Third party ownership and other financial incentives do not have significant interactions with rebate programs. In addition, it is worth noting that solar resource availability does not play an important role in explaining rebate treatment effect variation.

Several caveats are warranted. Most rebate programs have declining rate schedules as the prices of PV installations are expected to fall over time and this design reduces the overall program cost. During early stage of the program, the rebate level is high but adoption is low due to low demand and an underdeveloped market (Hughes and Podolefsky, 2015). For example, the California Solar

Initiative offers a rebate program where the initial rebate rate is \$2.50/W when the total installation capacity is under 70 MW, and gradually declines to \$0.20/W when the total installation capacity is above 350MW (Hughes and Podolefsky, 2015). Such design can help support early installers to overcome these barriers (Hughes and Podolefsky, 2015). Both causal forests and linear models in the analysis seem to support the theory in that the existence of rebate program matters, but the rebate level is less or not as important. The nonlinear effect of rebate levels uncovered by the analysis here is in contrast with the Crago and Chernyakhovskiy (2017) study, which adopts linear models with continuous measure of rebate treatment as \$ per watt and finds additional \$1 per watt of rebate is expected to increase annual installed capacity by 47.2%. They interpret their estimate as an additional 124.7 MW of PV capacity throughout Northeast US over the year 2005-2012 if the rebates had been \$1 per watt higher than the actual rates. Further analysis can be done to disaggregate the impact of rebate program existence and additional rebate level (\$/W) to support better cost benefit analysis.

Finally, the causal impact of rebate programs on solar installation are identified and estimated and tested with robustness checks. The relationships between various factors and treatment effect variation illustrated are contemporaneous correlations and by no means causal relations. Nevertheless, the empirical findings in the analysis can help policy makers to identify ways to complement or improve rebate program effectiveness in their regions and encourage the transition to cleaner residential energy systems.

Bibliography

Acemoglu, D., P. Aghion, L. Bursztyn, and D. Hemous (2012). The environment and directed technical change. *The American Economic Review 102*(1), 131–166.

Alcott, B. (2005). Jevons' paradox. *Ecological economics 54*(1), 9–21.

Amigues, J.-P., A. A. Le Kama, and M. Moreaux (2015). Equilibrium transitions from non-renewable energy to renewable energy under capacity constraints. *Journal of Economic Dynamics and Control 55*, 89–112.

Angrist, J. D. and J.-S. Pischke (2008). *Mostly harmless econometrics: An empiricist's companion*. Princeton university press.

Ansar, J. and R. Sparks (2009). The experience curve, option value, and the energy paradox. *Energy Policy 37*(3), 1012–1020.

Association, S. E. I. (2018). Solar industry research data.

Athey, S. and G. Imbens (2016). Recursive partitioning for heterogeneous causal effects. *Proceedings of the National Academy of Sciences 113*(27), 7353–7360.

Austin, P. C. (2011). An introduction to propensity score methods for reducing the effects of confounding in observational studies. *Multivariate behavioral research 46*(3), 399–424.

Austin, P. C. and E. A. Stuart (2015). Moving towards best practice when using inverse probability of treatment weighting (iptw) using the propensity score to estimate causal treatment effects in observational studies. *Statistics in medicine 34*(28), 3661–3679.

Azevedo, I. M. (2014). Consumer end-use energy efficiency and rebound effects. *Annual Review of Environment and Resources 39*, 393–418.

Azoulay, P., W. Ding, and T. Stuart (2009). The impact of academic patenting on the rate, quality and direction of (public) research output. *The Journal of Industrial Economics 57*(4), 637–676.

Barnow, B. S., G. G. Cain, A. S. Goldberger, et al. (1980). *Issues in the analysis of selectivity bias*. University of Wisconsin, Inst. for Research on Poverty.

Basu, K. (1995). Stackelberg equilibrium in oligopoly: an explanation based on managerial incentives. *Economics Letters 49*(4), 459–464.

Bauner, C. and C. L. Crago (2015). Adoption of residential solar power under uncertainty: Implications for renewable energy incentives. *Energy Policy 86*, 27–35.

Bertrand, M., B. Crépon, A. Marguerie, and P. Premand (2017). Contemporaneous and post-program impacts of a public works program: Evidence from côte d'ivoire. *Working paper*.

Bezdek, R. H., A. S. Hirshberg, and W. H. Babcock (1979). Economic feasibility of solar water and space heating. *Science 203*(4386), 1214–1220.

Binswanger, M. (2001). Technological progress and sustainable development: what about the rebound effect? *Ecological economics 36.1*, 119–132.

Bloem, M., T. Alpcan, and T. Başar (2007). A stackelberg game for power control and channel allocation in cognitive radio networks. In *Proceedings of the 2nd international conference on Performance evaluation methodologies and tools*, pp. 4. ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering).

Bollinger, B. and K. Gillingham (2012a). Peer effects in the diffusion of solar photovoltaic panels. *Marketing Science 31*(6), 900–912.

Bollinger, B. and K. Gillingham (2012b). Peer effects in the diffusion of solar photovoltaic panels. *Marketing Science 31*(6), 900–912.

Borenstein, S. (2009). To what electricity price do consumers respond? residential demand elasticity under increasing-block pricing. *Preliminary Draft April 30*.

Borenstein, S. and J. Bushnell (1999). An empirical analysis of the potential for market power in california's electricity industry. *The Journal of Industrial Economics 47*(3), 285–323.

Breiman, L. (2001). Random forests. *Machine learning 45*(1), 5–32.

Bresnahan, T. F. (1989). Empirical studies of industries with market power. *Handbook of industrial organization 2*, 1011–1057.

Bronin, S. C. (2009). Solar rights. *BUL Rev. 89*, 1217.

Büchlmann, P. and B. Yu (2002). Analyzing bagging. *Annals of Statistics*, 927–961.

Bureau of Economic Analysis (2017). Regional data.

Burns, J. E. and J.-S. Kang (2012). Comparative economic analysis of supporting policies for residential solar pv in the united states: Solar renewable energy credit (srec) potential. *Energy Policy 44*, 217–225.

Cairns, R. D. and P. Lasserre (1986). Sectoral supply of minerals of varying quality. *The Scandinavian Journal of Economics*, 605–626.

Carley, S. (2009). State renewable energy electricity policies: An empirical evaluation of effectiveness. *Energy policy 37*(8), 3071–3081.

Cho, D.-S., D.-J. Kim, and D. K. Rhee (1998). Latecomer strategies: evidence from the semiconductor industry in japan and korea. *Organization science 9*(4), 489–505.

Crago, C. L. and I. Chernyakhovskiy (2017). Are policy incentives for solar power effective? evidence from residential installations in the northeast. *Journal of Environmental Economics and Management 81*, 132–151.

Curtis, L. H., B. G. Hammill, E. L. Eisenstein, J. M. Kramer, and K. J. Anstrom (2007). Using inverse probability-weighted estimators in comparative effectiveness analyses with observational databases. *Medical care 45*(10), S103–S107.

De'ath, G. and K. E. Fabricius (2000). Classification and regression trees: a powerful yet simple technique for ecological data analysis. *Ecology 81*(11), 3178–3192.

Delmas, M., M. V. Russo, and M. J. Montes-Sancho (2007). Deregulation and environmental differentiation in the electric utility industry. *Strategic Management Journal 28*(2), 189–209.

DeMiguel, V. and H. Xu (2009). A stochastic multiple-leader stackelberg model: analysis, computation, and application. *Operations Research 57*(5), 1220–1235.

Domar, E. D. (1962). On total productivity and all that. *Journal of Political Economy 70*(6), 597–608.

Dong, C. and V. Rai (2014). Optimal subsidy design: Is california solar initiative over-subsidizing or under-subsidizing? *World (le axis) 30000*, 40000.

Dormann, C. F., J. Elith, S. Bacher, C. Buchmann, G. Carl, G. Carré, J. R. G. Marquéz, B. Gruber, B. Lafourcade, P. J. Leitão, et al. (2013). Collinearity: a review of methods to deal with it and a simulation study evaluating their performance. *Ecography 36*(1), 27–46.

Drake, C. (1993). Effects of misspecification of the propensity score on estimators of treatment effect. *Biometrics*, 1231–1236.

Energy Information Administration (2013). Status and outlook for shale gas and tight oil development in the u.s.

Energy Information Administration (2017). Monthly energy review.

EPA. Understanding third-party ownership financing structures for renewable energy.

Faiers, A. and C. Neame (2006). Consumer attitudes towards domestic solar power systems. *Energy Policy 34*(14), 1797–1806.

Faiers, A., C. Neame, and M. Cook (2007). The adoption of domestic solar-power systems: Do consumers assess product attributes in a stepwise process? *Energy Policy 35*(6), 3418–3423.

Fischer, C., C. Withagen, and M. Toman (2004). Optimal investment in clean production capacity. *Environmental and Resource Economics 28*(3), 325–345.

Freeing the Grid (2017). Freeing the grid.

Friedman, J., T. Hastie, and R. Tibshirani (2001). *The elements of statistical learning*, Volume 1. Springer series in statistics New York.

Friedman, J. H. and J. J. Meulman (2003). Multiple additive regression trees with application in epidemiology. *Statistics in medicine 22*(9), 1365–1381.

Fudenberg, D. and J. Tirole (1983). Capital as a commitment: Strategic investment to deter mobility. *Journal of Economic Theory 31*(2), 227–250.

Gillingham, K. (2012). Selection on anticipated driving and the consumer response to changing gasoline prices. working paper, Unpublished. Available at `http://www.idep.eco.usi.ch/paper-gillingham-186992.pdf`.

Gillingham, K., D. Rapson, and G. Wagner (2016). The rebound effect and energy efficiency policy. *Review of Environmental Economics and Policy 10.1*, 68–88.

Greene, D. L. (2012). Rebound 2007: analysis of us light-duty vehicle travel statistics. *Energy Policy 41*, 14–28.

Greening, L. A., D. L. Greene, and C. Difiglio (2000). Energy efficiency and consumption - the rebound effect -a survey. *Energy policy 28*(6), 389–401.

Guertin, C., S. C. Kumbhakar, and A. K. Duraiappah (2003). *Determining demand for energy services: investigating income-driven behaviours*. International Institute for Sustainable Development.

Hansen, J., M. Sato, R. Ruedy, P. Kharecha, A. Lacis, R. Miller, L. Nazarenko, K. Lo, G. Schmidt, G. Russell, et al. (2007). Dangerous human-made interference with climate: a giss modele study. *Atmospheric chemistry and physics 7*(9), 2287–2312.

Harder, V. S., E. A. Stuart, and J. C. Anthony (2010). Propensity score techniques and the assessment of measured covariate balance to test causal associations in psychological research. *Psychological methods 15*(3), 234.

He, X., A. Prasad, and S. P. Sethi (2009). Cooperative advertising and pricing in a dynamic stochastic supply chain: Feedback stackelberg strategies. *Production and Operations Management 18*(1), 78–94.

Hirano, K., G. W. Imbens, and G. Ridder (2003). Efficient estimation of average treatment effects using the estimated propensity score. *Econometrica 71*(4), 1161–1189.

Holland, M. M., C. M. Bitz, and B. Tremblay (2006). Future abrupt reductions in the summer arctic sea ice. *Geophysical research letters 33*(23).

Huang, C. and J. Townshend (2003). A stepwise regression tree for nonlinear approximation: applications to estimating subpixel land cover. *International Journal of Remote Sensing 24*(1), 75–90.

Hughes, J. E. and M. Podolefsky (2015). Getting green with solar subsidies: evidence from the california solar initiative. *Journal of the Association of Environmental and Resource Economists 2*(2), 235–275.

Imai, K. (2005). Do get-out-the-vote calls reduce turnout? the importance of statistical methods for field experiments. *American Political Science Review 99*(2), 283–300.

Imai, K., G. King, and E. A. Stuart (2008). Misunderstandings between experimentalists and observationalists about causal inference. *Journal of the royal statistical society: series A (statistics in society) 171*(2), 481–502.

International Energy Agency (2015a). Key world energy statistics.

International Energy Agency (2015b). World energy outlook 2015 factsheet.

Jevons, W. S. (1906). *The coal question: an inquiry concerning the progress of the nation, and the probable exhaustion of our coal-mines*. Macmillan.

Jones, P., U. K. Vyas, N. Taylor, and M. J. Kipp (2010). Residential energy efficiency: a model methodology for determining performance outcomes. *Real Estate Issues 35*(2), 41–48.

Khazzoom, J. D. (1980). Economic implications of mandated efficiency in standards for household appliances. *The Energy Journal 1.4*, 21–40.

Korcaj, L., U. J. Hahnel, and H. Spada (2015). Intentions to adopt photovoltaic systems depend on homeowners' expected personal gains and behavior of peers. *Renewable Energy 75*, 407–415.

Krasko, V. A. and E. Doris (2013). State distributed pv policies: Can low cost (to government) policies have a market impact? *Energy policy 59*, 172–181.

Lab, N. R. E. (2012). The open pv project.

League of Conservation Voters (2016). National environmental scorecard.

Lee, B. K., J. Lessler, and E. A. Stuart (2010). Improving propensity score weighting using machine learning. *Statistics in medicine 29*(3), 337–346.

Lee, C.-C. and J.-D. Lee (2010). A panel data analysis of the demand for total energy and electricity in oecd countries. *The Energy Journal*, 1–23.

Lenton, T. M., H. Held, E. Kriegler, J. W. Hall, W. Lucht, S. Rahmstorf, and H. J. Schellnhuber (2008). Tipping elements in the earth's climate system. *Proceedings of the national Academy of Sciences 105*(6), 1786–1793.

Li, H. and C. E. Carrión-Flores (2017). An analysis of the energy star® program in alachua county, florida. *Ecological Economics 131*, 98–108.

Lindsay, R. and J. Zhang (2005). The thinning of arctic sea ice, 1988–2003: Have we passed a tipping point? *Journal of Climate 18*(22), 4879–4894.

Mansur, E. T. (2013). Prices versus quantities: environmental regulation and imperfect competition. *Journal of Regulatory Economics 44*(1), 80–102.

McCaffrey, D. F., B. A. Griffin, D. Almirall, M. E. Slaughter, R. Ramchand, and L. F. Burgette (2013). A tutorial on propensity score estimation for multiple treatments using generalized boosted models. *Statistics in medicine 32*(19), 3388–3414.

McCaffrey, D. F., G. Ridgeway, and A. R. Morral (2004). Propensity score estimation with boosted regression for evaluating causal effects in observational studies. *Psychological methods 9*(4), 403.

Mullainathan, S. and J. Spiess (2017). Machine learning: an applied econometric approach. *Journal of Economic Perspectives 31*(2), 87–106.

Murray, A. G. and B. F. Mills (2011). Read the label! energy star appliance label awareness and uptake among us consumers. *Energy Economics 33.6*, 1103–1110.

National Research Council (2002). Inevitable surprises. *Natl Acad Press, Washington, DC*.

Nevo, A. and A. M. Rosen (2012). Identification with imperfect instruments. *Review of Economics and Statistics 94*(3), 659–671.

Nordhaus, W. D., H. Houthakker, and R. Solow (1973). The allocation of energy resources. *Brookings papers on economic activity 1973*(3), 529–576.

of State Legislature, N. C. (2017). State renewable portfolio standards and goals.

Olsen, T. E. (1989). Capital investments and resource extraction from non-identical deposits. *Journal of Environmental Economics and Management 17*(2), 127–139.

OpenEI.org (2011). U.s. electric utility companies and rates: Look-up by zipcode (feb 2011).

OShaughnessy, E. J., C. M. Volpi, J. S. Heeter, and J. J. Cook (2017). Status and trends in the us voluntary green power market (2016 data). Technical report, National Renewable Energy Lab.(NREL), Golden, CO (United States).

Pachauri, R. K., M. R. Allen, V. R. Barros, J. Broome, W. Cramer, R. Christ, J. A. Church, L. Clarke, Q. Dahe, P. Dasgupta, et al. (2014). *Climate change 2014: synthesis report. Contribution of Working Groups I, II and III to the fifth assessment report of the Intergovernmental Panel on Climate Change*. IPCC.

Painuly, J. P. (2001). Barriers to renewable energy penetration; a framework for analysis. *Renewable energy 24*(1), 73–89.

Pivovarova, M. (2013). *Peer Effects in the Classroom: Evidence from New Peers*. Ph. D. thesis, University of Toronto.

Powell, S. G. and S. S. Oren (1989). The transition to nondepletable energy: social planning and market models of capacity expansion. *Operations research 37*(3), 373–383.

Qiu, Y. (2014). Energy efficiency and rebound effects: an econometric analysis of energy demand in the commercial building sector. *Environmental and Resource Economics 59.2*, 295–335.

Rai, V. and S. A. Robinson (2013). Effective information channels for reducing costs of environmentally-friendly technologies: evidence from residential pv markets. *Environmental Research Letters 8*(1), 014044.

Ridgeway, G., D. McCaffrey, A. Morral, L. Burgette, and B. A. Griffin (2006). Toolkit for weighting and analysis of nonequivalent groups: A tutorial for the twang package. *Santa Monica, CA: RAND Corporation*.

Robins, J. M., M. A. Hernan, and B. Brumback (2000). Marginal structural models and causal inference in epidemiology.

Rogers, E. M. (2010). *Diffusion of innovations*. Simon and Schuster.

Rosenbaum, P. R. and D. B. Rubin (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika 70*(1), 41–55.

Rosenbaum, P. R. and D. B. Rubin (1984). Reducing bias in observational studies using subclassification on the propensity score. *Journal of the American statistical Association 79*(387), 516–524.

Rosenbaum, P. R. and D. B. Rubin (1985). Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. *The American Statistician 39*(1), 33–38.

Rubin, D. B. (1978). Bayesian inference for causal effects: The role of randomization. *The Annals of statistics*, 34–58.

Rubin, D. B. (2001). Using propensity scores to help design observational studies: application to the tobacco litigation. *Health Services and Outcomes Research Methodology 2*(3), 169–188.

Russill, C. and Z. Nyssa (2009). The tipping point trend in climate change communication. *Global environmental change 19*(3), 336–344.

Sacerdote, B. et al. (2011). Peer effects in education: How might they work, how big are they and how much do we know thus far? *Handbook of the Economics of Education 3*(3), 249–277.

Sarzynski, A., J. Larrieu, and G. Shrimali (2012). The impact of state financial incentives on market deployment of solar technology. *Energy Policy 46*, 550–557.

Scarpa, R. and K. Willis (2010). Willingness-to-pay for renewable energy: Primary and discretionary choice of british households' for micro-generation technologies. *Energy Economics 32*(1), 129–136.

Schelly, C. (2014). Residential solar electricity adoption: what motivates, and what matters? a case study of early adopters. *Energy Research & Social Science 2*, 183–191.

Schimek, P. (1996). Gasoline and travel demand models using time series and cross-section data from united states. *Transportation Research Record: Journal of the Transportation Research Board 1558*, 83–89.

Schwarz, P. M. and T. N. Taylor (1995). Cold hands, warm hearth?: climate, net takeback, and household comfort. *The Energy Journal*, 41–54.

Small, K. A. and K. Van Dender (2007). Fuel efficiency and motor vehicle travel: the declining rebound effect. *The Energy Journal*, 25–51.

Sommerfeld, J., L. Buys, K. Mengersen, and D. Vine (2017). Influence of demographic variables on uptake of domestic solar photovoltaic technology. *Renewable and Sustainable Energy Reviews 67*, 315–323.

Sorrell, S., J. Dimitropoulos, and M. Sommerville (2009). Empirical estimates of the direct rebound effect: A review. *Energy policy 37.4*, 1356–1371.

Spencer, B. J. and J. A. Brander (1992). Pre-commitment and flexibility: Applications to oligopoly theory. *European Economic Review 36*(8), 1601–1626.

Stern, N. (2013). The structure of economic modeling of the potential impacts of climate change: grafting gross underestimation of risk onto already narrow science models. *Journal of Economic Literature 51*(3), 838–859.

Stock, J. H. and M. Yogo (2002). Testing for weak instruments in linear iv regression.

Strobl, C., J. Malley, and G. Tutz (2009). An introduction to recursive partitioning: rationale, application, and characteristics of classification and regression trees, bagging, and random forests. *Psychological methods 14*(4), 323.

Tokarska, K. B., N. P. Gillett, A. J. Weaver, V. K. Arora, and M. Eby (2016). The climate response to five trillion tonnes of carbon. *Nature climate change*.

Tsur, Y. and A. Zemel (2011). On the dynamics of competing energy sources. *Automatica 47*(7), 1357–1365.

U.S. Energy Information Administration (2013a). Residential energy consumption survey (recs) 2009 technical documentation summary. *U.S. Department of Energy*. Available at https://www.eia.gov/consumption/residential/methodology/2009/pdf/techdoc-summary010413.pdf.

U.S. Energy Information Administration (2013b). Residential energy consumption survey (recs): Using the 2009 microdata file to compute estimates and standard errors (rses). *U.S. Department of Energy*. Available at http://www.eia.gov/consumption/residential/methodology/2009/pdf/using-microdata-022613.pdf.

U.S. Energy Information Administration (2015). Drivers of u.s. household energy consumption, 1980-2009. *U.S. Department of Energy*. Available at https://www.eia.gov/analysis/studies/buildings/households/.

U.S. Environmental Protection Agency (2015). Office of atmospheric programs climate protection partnerships: 2013 annual report. *U.S. Environmental Protection Agency.*. Available at https://www.energystar.gov/ia/partners/publications/pubdocs/ENERGYSTAR_2013AnnualReport-508.pdf.

Van Benthem, A., K. Gillingham, and J. Sweeney (2008). Learning-by-doing and the optimal solar policy in california. *The Energy Journal*, 131–151.

Van Damme, E. and S. Hurkens (1999). Endogenous stackelberg leadership. *Games and Economic Behavior 28*(1), 105–129.

Wager, S. and S. Athey (2017). Estimation and inference of heterogeneous treatment effects using random forests. *Journal of the American Statistical Association* (just-accepted).

Wan, R. and J. R. Boyce (2014). Non-renewable resource stackelberg games. *Resource and Energy Economics 37*, 102–121.

Wang, M. and J. Zhao (2013). Monopoly extraction of a nonrenewable resource facing capacity constrained renewable competition. *Economics Letters 120*(3), 503–508.

Watkins, S., M. Jonsson-Funk, M. A. Brookhart, S. A. Rosenberg, T. M. O'shea, and J. Daniels (2013). An empirical comparison of tree-based methods for propensity score estimation. *Health services research 48*(5), 1798–1817.

Weitzman, M. L. (2009). On modeling and interpreting the economics of catastrophic climate change. *The Review of Economics and Statistics 91*(1), 1–19.

Williams, R. (2016). Understanding and interpreting generalized ordered logit models. *The Journal of Mathematical Sociology 40*(1), 7–20.

Winton, M. (2006). Does the arctic sea ice have a tipping point? *Geophysical Research Letters 33*(23).

Wirl, F. (1991). (monopolistic) resource extraction and limit pricing: The market penetration of competitively produced synfuels. *Environmental and Resource Economics 1*(2), 157–178.

Wolfram, C. D. (1999). Measuring duopoly power in the british electricity spot market. *American Economic Review 89*(4), 805–826.

Wolske, K. S., P. C. Stern, and T. Dietz (2017). Explaining interest in adopting residential solar photovoltaic systems in the united states: Toward an integration of behavioral theories. *Energy research & social science 25*, 134–151.

A Appendix - Chapter 1

A.1 List of notations and functional assumptions

A summary of notation and assumed functional forms used in the analysis is as follows:

x_t: production level of the dirty sector in period t;

y_t : production level of the clean sector in period t;

I_t : investment level in clean knowledge capital in period t;

K_t : cumulative clean capital investment in period t;

S_t : pollution stock in period t;

$C^y(AK)$: unit cost of clean production $C^y(K) = M - AK$ with an upper bound of M and a lower bound of c^y;

A: a positive constant reflecting knowledge capital efficiency in the clean cost function;

c^x: constant unit cost of dirty production;

c^y: minimum unit cost of clean production, with $M \gg c^x > c^y$;

$f(I)$: cost function of capital investment $f(I) = \gamma I^2$, where γ is a positive and constant cost parameter;

$P(\cdot)$: inverse demand function $P(q) = \alpha - \beta q$, where $\alpha, \beta > 0$;

r: constant and positive discount rate;

δ: rate of pollution sequestration;

η: emissions intensity (emissions per unit of dirty production);

τ: dirty production tax rate;

θ: clean production subsidy rate;

ρ: clean investment proportional subsidy rate.

A.2 Proof of Proposition 1

In the stage where both the leader and follower produce, the follower's maximization problem is

$$V_2^F(T,K) = \max_{y_t, I_t} \int_0^T e^{-rt} \left[P(x_t + y_t)y_t - (M - AK_t)y_t - \gamma I_t^2 \right] dt + V_3^F(t_2, \overline{K})$$

subject to

$$\dot{K}_t = I_t$$

$$y_t, I_t \geqslant 0, K_T = \overline{K} = \frac{M - c^y}{A}$$

In this proof, we normalize the starting time of this stage to $t = 0$ and denote the duration of this stage as T. At $t = T$, the clean capital stock reaches its steady state level, the clean production rate is $y_T^* = \frac{\alpha - 3c^y + 2c^x}{4\beta}$, and the coal production rate is $x_T^* = \frac{\alpha + c^y - 2c^x}{2\beta}$. Since the system dynamics do not involve y_t, we can derive the optimal y_t given x_t as

$$y(K_t \mid x_t) = \frac{1}{2\beta}\left[\alpha - \beta x_t - M + AK_t\right].$$

The leader's maximization problem is:

$$V_2^L(t_2, K) = \max_{x_t} \int_0^T e^{-rt}\left[P(x_t + y^*(K_t \mid x_t))x_t - c^x x_t\right] dt + V_3^F(t_2, \overline{K}).$$

Solving this problem yields the leader's optimal production level:

$$x_t^*(K_t) = \frac{1}{2\beta}\left[-AK_t + \alpha + M - 2c^x\right]. \tag{A.1}$$

Hence, the feedback production strategy of the follower is

$$y^*(K_t) = \frac{1}{2\beta}\left[\frac{3}{2}AK_t + \frac{\alpha}{2} - \frac{3}{2}M + c^x\right]. \tag{A.2}$$

Plugging $x^*(K)$ and $y^*(K)$ into the follower's problem, the follower's objective function becomes

$$V_2^F(T, K_t) = \max_{y_t, I_t} \int_0^T e^{-rt}\left[\frac{(3AK_t - 3M + \alpha + 2c^x)^2}{16\beta} - \gamma I_t^2\right] dt + e^{-rT}\frac{(-3c^y + \alpha + 2c^x)^2}{16\beta}.$$

Let $R_t = 3AK_t - 3M + \alpha + 2c^x$. The follower's problem can be rewritten as

$$V_2^F(T, R_t) = \max_{I_t} \int_0^T e^{-rt}\left[\frac{R_t^2}{16\beta} - \gamma I_t^2\right] dt + e^{-rT}\frac{R_T^2}{16\beta},$$

subject to

$$\dot{R}_t = 3AI_t, R_T = -3c^y + \alpha + 2c^x. \tag{A.3}$$

Applying the Linear Quadratic Regulator method, we form the Hamiltonian and evaluate first order conditions:

$$H_t = e^{-rt}\left(\frac{R_t^2}{16\beta} - \gamma I_t^2\right) + 3AI_t\lambda_t,$$

$$\frac{\partial H_t}{\partial I_t} = e^{-rt}(-2\gamma I_t) + 3A\lambda_t = 0 \Rightarrow I_t = \frac{e^{rt}3A}{2\gamma}\lambda_t, \tag{A.4}$$

$$\dot{\lambda}_t = -\frac{\partial H_t}{\partial R_t} = -e^{-rt}\frac{R_t}{8\beta}. \tag{A.5}$$

Define a transition matrix $P(t)$ such that $\lambda_t = -P(t)R_t$, and λ_t and R_t satisfy equation (A.4) and (A.5). The "feedback" investment strategy is

$$I^*(R) = \frac{e^{rt}3A}{2\gamma}\lambda_t = -\frac{e^{rt}3A}{2\gamma}P(t)R. \tag{A.6}$$

Totally differentiate both sides of the equation $\lambda_t = -P(t)R_t$ yielding

$$\dot{\lambda}_t = -\dot{P}(t)R_t - P(t)\dot{R}_t. \tag{A.7}$$

Substitute equation (A.4), (A.5), $\lambda_t = -P(t)R_t$ and $\dot{R}_t = 3AI_t$ in (A.7), yielding:

$$e^{-rt}\frac{R_t}{8\beta} = \dot{P}(t)R_t - P(t)^2\frac{e^{rt}9A^2}{2\gamma}R_t,$$

$$\frac{e^{-rt}}{8\beta} = \dot{P}(t) - P(t)^2\frac{e^{rt}9A^2}{2\gamma}. \tag{A.8}$$

Solving the above differential equation for P(t) yields:

$$P(t) = \frac{e^{-rt}\gamma}{18A^2}\left(-2r - D + \frac{4D}{2 + De^{\frac{1}{2}Dt}C[1]}\right), \tag{A.9}$$

where D = $\sqrt{4r^2 - \frac{9A^2}{\beta\gamma}}$ and C[1] is some unknown constant.

Plugging the expression for $P(t)$ into the differential equation (A.6) to get $\dot{R} = I(R)$, we can solve for $R(t)$ as the function of two unknown parameters C[1] and C[2]. These two parameters are determined by the boundary conditions $R(t=0)=R_0$ and $R(t=T)=R_T$. Finally, plugging in C[1] and C[2] into equation (A.6), we can solve the open loop form of the investment strategy as

$$I(R,t;T)=\frac{R}{12A}\left[2r-D\left(-1+\frac{2}{1-\frac{R_0-R_Te^{\frac{1}{4}(D-2r)T}}{R_0e^{\frac{DT}{2}}-R_Te^{\frac{1}{4}(D-2r)T}}}\right)\right],$$

where $R_0=3AK_0-3M+\alpha+2c^x$, $R_T=-3c^y+\alpha+2c^x$.

In order to derive the optimal duration T^*, we evaluate $I(R,t;T)=0$ at $t=T$ and $R=R_T$ because, by definition, the optimal investment level should be at zero when $t=T$ and $R=R_T$. The following condition defines the optimal duration of transition T^*:

$$\frac{R_0}{R_T}=\frac{e^{\frac{DT^*}{2}}(D+2r)+D-2r}{2De^{\frac{1}{4}(D+2r)T^*}}. \tag{A.10}$$

Finally, in order to get feedback control strategy for the follower, we set $t=0$ and $R_0=R$ in the open loop form of the investment strategy:

$$I(R,\Delta)=\frac{R}{12A}\left[2r-D\left(-1+\frac{2}{1-\frac{R-R_Te^{\frac{1}{4}(D-2r)\Delta}}{Re^{\frac{D}{2}\Delta}-R_Te^{\frac{1}{4}(D-2r)\Delta}}}\right)\right], \tag{A.11}$$

where $\Delta=T-t$, which is the time remaining to reach steady state from the current time, is defined by

$$\frac{R}{R_T}=\frac{e^{\frac{D}{2}\Delta}(D+2r)+D-2r}{2De^{\frac{1}{4}(D+2r)\Delta}}. \tag{A.12}$$

Equation (A.11) and (A.12) jointly determine the feedback investment strategy as function of R. The feedback investment strategy does not have an explicit form, but the implicit form can be evaluated numerically.

In terms of shadow value λ, we go back to equation (A.9)

$$P(t)=\frac{e^{-rt}\gamma}{18A^2}(-2r-D+\frac{4D}{2+De^{\frac{1}{2}Dt}C[1]})=-\frac{\lambda_t}{R_t};$$

$$-\frac{\lambda_t}{S_t}\frac{18A^2}{e^{-rt}\gamma}+(2r+D)=\frac{4D}{2+De^{\frac{1}{2}Dt}C[1]}.$$

Since additional capital does not increase the value function at time T, $\lambda_T = 0$ holds. Hence, we can derive the expression of λ_t as function of R and t

$$\lambda_t = \frac{e^{-rt}\left(e^{D(T-t)/2}-1\right)(4r^2-D^2)\gamma}{18A^2\left[(D+2r)e^{D(T-t)/2}+D-2r\right]}R_t.$$

For the feedback strategy, substituting $t = 0$ (Δ is the time left to reach the steady state) yields

$$\lambda_t = \frac{\left(e^{D\Delta/2}-1\right)(4r^2-D^2)\gamma}{18A^2\left[(D+2r)e^{D\Delta/2}+D-2r\right]}R_t. \tag{A.13}$$

The shadow value increases with R_t as its coefficient is always positive for $\Delta > 0$. But the coefficient decreases as Δ gets smaller: as the producer approaches the steady state, the value of capital declines. The value of R_t and Δ have opposite effects on the shadow value as the system approaches the steady state. Since the ending shadow value of knowledge capital at T is zero, the effect of Δ outweighs the effect of R_t eventually. Therefore, the shadow value of clean knowledge capital increases initially and gradually declines to zero when reaching the steady state.

According to equation (A.6), the investment strategy can be written as

$$I_t^* = \frac{e^{rt}3A}{2\gamma}\lambda_t.$$

Hence, the feedback investment rate changes with the shadow value: it increase with R first, then gradually declines to zero.

Note that the above feedback equation does not hold when $K = \frac{3M-\alpha-2c^x}{3A}$, because when $R = 0$ the denominator of the fraction in equation (A.11) becomes zero. Hence, the above equation (A.11) is only valid for strictly interior solutions. $R < 0$ also does not fit the above feedback strategy. To see why, consider the case where $R_0 < 0$ (i.e. $K < \frac{3M-\alpha-2c^x}{3A}$): according to equation (A.10), $e^{\frac{DT^*}{2}}(D+2r) < 2r-D \Rightarrow e^{\frac{DT^*}{2}} < \frac{2r-D}{2r+D}$ must hold. Since $\frac{2r-D}{2r+D} < 1$, the optimal T^* would be negative. Hence, the above feedback investment strategy only holds if $R > 0$ (i.e. $K > \frac{3M-\alpha-2c^x}{3A}$). If the initial capital $K_0 = 0$, then the initial clean production cost M should be sufficiently low $M < \frac{\alpha+2c^x}{3}$ for the clean producer to immediately start producing.

This restriction matches with the feedback clean production strategy, because if $K < \frac{3M-\alpha-2c^x}{3A}$, the clean production rate becomes negative.

In summary, the above feedback strategies only hold when $K > \frac{3M-\alpha-2c^x}{3A}$ or $M < \frac{\alpha+2c^x}{3}$ when $K_0 = 0$. □

A.3 Proof of Proposition 2

In the Stackelberg model, the leader announces his strategy (i.e. production rate) as a function of the clean capital, then the follower chooses his optimal response to the leader's strategy. When the clean production cost $C^y(K)$ reaches the level of the dirty monopoly price P_0, the clean producer would have incentives to produce. If the leader were to produce at the monopoly level x_0 for capital levels higher than that for which $C^y(K) = P_0$, then the follower's optimal response would be to start production at that time point. If the follower were to enter the market (i.e. $y > 0$), the optimal strategy for the leader would be to produce at the feedback rate x^* in Proposition 1 given by equation (A.1) in the following time period. However, the feedback dirty production rate x^* would result in a price level that is lower than the clean production cost, which would subsequently force the clean producer to stop producing. Anticipating such reaction from the follower, the leader's optimal strategy is to set the market price equal to the clean production cost, which generates the highest profit for the leader while deterring the follower's entry. Because the leader always announces his strategy before the follower does and the follower's entry decision is reversible (i.e. the follower can enter and exit the market with no barrier), the leader needs to deter the follower's entry constantly. This entry deterrence continues until the market price given the feedback strategy $x^*(K)$ (equation A.1) is no longer lower than the clean production cost $C^y(K)$. The clean capital stock at this point is $K = \frac{3M-\alpha-2c^x}{3A}$, which is the also the minimum capital stock for simultaneous clean investment and production strategies.□

A.4 Proof of Proposition 3

The dirty producer is the monopoly in the market before transition occurs. The clean producer can invest in capital and drive down its production cost before entering the market. For the case where

$K \leqslant \frac{3M-\alpha-2c^x}{3A}$ (or $M \geqslant \frac{\alpha+2c^x}{3}$ when $K_0 = 0$), we can set up the following problem:

$$V_1^F(K_0) = \max_{I_t} \int_0^{t_1} e^{-rt}\left(-\gamma I_t^2\right) dt + e^{-rt_1} V_2^F(t_1, K_{t_1}),$$

subject to

$$\dot{K}_t = I_t,$$

$$K_{t_1} = \frac{3M-\alpha-2c^x}{3A},$$

where $V_2^F(t_1, K_{t_1})$ is the value function given the feedback strategy from stage 2 of joint production and t_1 is the duration of the first stage. The Hamiltonian and its first order conditions are:

$$H_t = e^{-rt}\left(-\gamma I_t^2\right) + \lambda_t I_t;$$

$$\frac{\partial H_t}{\partial I_t} = -e^{-rt}(2\gamma I_t) + \lambda_t = 0 \Rightarrow I_t = \frac{e^{rt}}{2\gamma}\lambda_t; \tag{A.14}$$

$$\dot{\lambda}_t = -\frac{\partial H_t}{\partial K_t} = 0. \tag{A.15}$$

There should exist a matrix such that

$$I(K) = \frac{e^{rt}}{2\gamma}\lambda_t = -\frac{e^{rt}}{2\gamma}P(t)K, \tag{A.16}$$

where $P(t)$ is defined by $\lambda_t = -P(t)K_t$. Differentiate both sides to get $\dot{\lambda}_t = -\dot{P}(t)K_t - P(t)\dot{K}_t$. Substitute the equations to get

$$0 = -\dot{P}(t)K_t + P(t)^2\frac{e^{rt}}{2\gamma}K_t,$$

$$0 = -\dot{P}(t) + P(t)^2\frac{e^{rt}}{2\gamma}.$$

Solving the differential equation for $P(t)$ yields:

$$P(t) = \frac{-2r\gamma}{e^{rt} + 2r\gamma C[1]}. \tag{A.17}$$

Substitute $\lambda_t = -P(t)K_t$ into equation (A.17) to eliminate $P(t)$:

$$-\frac{\lambda_t}{K_t} = \frac{-2r\gamma}{e^{rt} + 2r\gamma C[1]},$$

and solve for C[1]:

$$C[1] = \frac{2r\gamma K_t - \lambda_t e^{rt}}{2r\gamma\lambda_t}.$$

Since C[1] is constant, we can equate the RHS at ($t = 0$, $K_t = K$) and ($t = t_1$, $K_t = K_{t_1}$). We know from equation (A.14) that λ_t is constant, hence:

$$\frac{2r\gamma K - \lambda}{2r\gamma\lambda} = \frac{2r\gamma K_{t_1} - \lambda_{t_1} e^{rt_1}}{2r\gamma\lambda},$$

and solving for λ :

$$\lambda = \frac{2r\gamma(K_{t_1} - K)}{e^{rt_1} - 1}. \tag{A.18}$$

Equation (A.18) shows the shadow value of the capital stock depends positively on the capital gap between the level at which the clean producer can profitably start producing and the current level of capital. It also depends negatively on the time remaining in the period t_1: if the producer will not start producing for a long time, knowledge capital is less valuable. The shadow value is also declining in the discount rate r and increasing the cost of acquiring more capital γ.

The derive the optimal duration t_1, we can make use of the transversality condition, which states that the discounted marginal value of the stock should be equal across the stage boundary:

$$\lambda_{t_1^*} = \lambda = \frac{2r\gamma(K_{t_1} - K)}{e^{rt_1^*} - 1} = e^{-rt_1^*}\frac{\partial V_2^F}{\partial K}|K = K_{t_1}.$$

Rearranging the above transversality condition to solve for t_1^* as

$$t_1^* = \frac{1}{r}ln\left(\frac{\frac{\partial V_2^F}{\partial K}|K = K_{t_1}}{\frac{\partial V_2^F}{\partial K}|K = K_{t_1} - 2r\gamma(K_{t_1} - K)}\right).$$

Substituting equation (A.18) into (A.16) to get the feedback investment rate

$$I(K,t;t_1) = \frac{r(K_{t_1} - K)}{e^{rt_1} - 1}.$$

Substitute the optimal t_1^* into the above feedback form to get the optimal feedback investment strategy:

$$I(K) = \frac{\frac{\partial V_2^F}{\partial K}|K = \hat{K}}{2\gamma} - r(\hat{K} - K). \tag{A.19}$$

□

A.5 Proof of Proposition 4

Recall in section 2, the steady state dirty production level is

$$x^* = \frac{\alpha + c^y - 2c^x}{2\beta}.$$

Given the pollution stock dynamics in equation (5) and the expression of steady state dirty production x^*, we derive the path of pollution stock growth over time as

$$S_t = e^{-t\delta}\left(S_0 - \frac{\eta x^*}{\delta}\right) + \frac{\eta x^*}{\delta}$$

where S_0 is the pollution stock level when the clean investment stops and market reaches steady state. The rate of pollution stock growth is

$$\dot{S}_t = e^{-t\delta}(\eta x^* - \delta S_0)$$

If $S_0 < \eta x^*/\delta$, then the pollution stock strictly increases in the Stackelberg steady state. As t increases, the pollution stock approaches $\eta x^*/\delta$ from below but never surpasses it.

If $S_0 \geqslant \eta x^*/\delta$, the pollution stock stays constant or gradually declines over time. As t increases, the pollution stock approaches $\eta x^*/\delta$ from above but never falls below it.

Therefore, if $\eta x^*/\delta \leqslant \overline{S}$ and $S_0 < \eta x^*/\delta$, an environmental disaster can be avoided without policy intervention.

If $\eta x^*/\delta > \overline{S}$ and $S_0 \geqslant \overline{S}$, the critical threshold would be met during or after the transition process and environmental disaster would happen.

Finally, if conditions are such that the clean producer never enters the market, then $x^* = x_0 = \frac{\alpha - c^x}{2\beta}$ (the monopoly production level) and $S_0 = 0$. The $S_0 < \eta x^*/\delta$ case above applies, and the threshold $\overline{S}$ is avoided only if the dirty monopoly production level is sufficiently low, i.e. $\eta x_0/\delta = \eta x^*/\delta \leqslant \overline{S}$.

B Appendix - Chapter 2

B.1 Derivation of the direct rebound effect

1. When $u_{sy} < 0$

The optimal $s(\eta)$ equates the marginal utility of appliance service with the marginal utility of spending on other goods as the result of electricity usage of the appliance (equation B.1).

$$u_s(s, y_2, x) = \frac{p}{\eta} u_y(s, y_2, x) \tag{B.1}$$

The optimal η is derived by considering the direct impact of investing in η on the utility in period 1 and also the indirect impact on expenditures through $s(\eta)$ in period 2. Hence, the condition for the optimal η is:

$$u_y(y_1, x) c_\eta = \delta u_s(s, y_2, x) \frac{\partial s(\eta)}{\partial \eta} - \delta p u_y(s, y_2, x) \left[\frac{1}{\eta} \frac{\partial s(\eta)}{\partial \eta} - \frac{s(\eta)}{\eta^2} \right] \tag{B.2}$$

Substituting equation (B.1) into equation (B.2) gives equation (B.3), which states that the marginal income impact of choosing higher efficiency appliance in period 1 should equal to the discounted marginal impact of changing appliance service level in response to higher efficiency in period 2.

$$u_y(y_1, x) c_\eta \eta = \delta u_s(s, y_2, x) s(\eta) \tag{B.3}$$

By differentiating both sides of equation (B.3) with respect to η, the effect of higher efficiency (η) on the optimal level of service demand (s) (i.e., the direct rebound effect) is derived. Assume the cost function of the appliance in question is linear in its efficiency level ($c_{\eta\eta} = 0$), then the expression of direct rebound effect in this model is

$$\frac{\partial s(\eta)}{\partial \eta} = \frac{c_\eta u_y(y_1, x) - \eta c_\eta^2 u_{yy}(y_1, x) - \delta p s^2 u_{sy}(s, y_2, x)/\eta^2}{\delta s \left(u_{ss}(s, y_2, x) - p u_{sy}(s, y_2, x)/\eta\right) + \delta u_s(s, y_2, x)} \tag{B.4}$$

2. When $\xi_{u_s} = 1$

If $\xi_{u_s} = 1$, the expression of $\partial s(\eta)/\partial \eta$ is no longer equation (B.4) as the denominator becomes zero. Differentiating equation (B.3) with respect to η gives

$$c_{\eta} u_y(y_1,x) - \eta c_{\eta}^2 u_{yy}(y_1,x) = \delta p s^2 u_{sy}(s,y_2,x)/\eta^2 \tag{B.5}$$

Equation (B.5) does not offer a clear indication of the sign of $\partial s(\eta)/\partial \eta$. When the third order derivatives of the cost function and the utility function are zeros, the derivative of equation (B.5) with respect to η is

$$c_{\eta} u_{yy}(y_1,x) = \frac{2\delta p}{\eta^2} u_{sy}(s,y_2,x) s(\eta) \frac{\partial s(\eta)}{\partial \eta}. \tag{B.6}$$

In the case where $u_{sy} < 0$, the sign of $\partial s(\eta)/\partial \eta$ is positive, and vice versa. This means if the marginal utility of appliance service is unit elastic, then decreasing marginal utility of appliance service with income yields positive direct rebound effect; increasing marginal utility of appliance service with income yields negative rebound effect. If the separability of appliance service and consumption holds ($u_{sy} = 0$), then the sign of $\partial s(\eta)/\partial \eta$ is ambiguous.

B.2 Full regression tables for Energy Star dishwasher and its frequency of use

Table 1: OLS Estimation Results for the Frequency of Using Dishwasher

Dependent Variable: Frequency of Using Dishwasher	Coeff.	S.E.
Energy Star Dishwasher	0.237**	(0.084)
House in urban area (=1)	-0.109	(0.061)
Age of house in 2010	-0.001	(0.001)
Number of years living in the house in 2010	-0.029	(0.021)
Age of dishwasher	0.014	(0.053)
Have microwave oven	-0.315	(0.260)
Number of stoves	0.018	(0.099)
Number of separate ovens	0.047	(0.078)
Frequency of cooking hot meals	0.143***	(0.028)
Had home energy audit before	0.090	(0.096)
Have Energy Star clothes washer	0.091	(0.056)
Have Energy Star frige	-0.086	(0.057)
Averge electricity price in 2009 (dollar/kWh)	-0.414	(0.736)
Householder lives with spouse or partner	0.359***	(0.076)
2009 gross household income	0.053*	(0.021)
2009 gross household income squared	-0.002*	(0.001)
Number of household members	0.234***	(0.024)
Education level	0.015	(0.018)
Own (=1) or Rent (=2) the house	0.064	(0.095)
Total square footage of the house	0.000**	(0.000)
ACEEE 2008	-0.100	(0.474)
ACEEE 2009	-0.102	(0.432)
AWE 2011	-0.006	(0.004)
Constant	1.750***	(0.404)
Observations	1761	
R^2	0.204	

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 2: Ordered Logit Estimation Results for the Frequency of Using Dishwasher

Dependent Variable: Frequency of Using Dishwasher	Coeff.	S.E.
Energy Star Dishwasher	0.401**	(0.143)
House in urban area (=1)	-0.137	(0.106)
Age of house in 2010	-0.002	(0.002)
Number of years living in the house in 2010	-0.038	(0.036)
Age of dishwasher	0.083	(0.090)
Have microwave oven	-0.536	(0.504)
Number of stoves	0.062	(0.162)
Number of separate ovens	0.104	(0.132)
Frequency of cooking hot meals	0.262***	(0.049)
Had home energy audit before	0.155	(0.169)
Have Energy Star clothes washer	0.169	(0.095)
Have Energy Star frige	-0.147	(0.098)
Averge electricity price in 2009 (dollar/kWh)	-1.223	(1.724)
Householder lives with spouse or partner	0.653***	(0.138)
Householder is male	-0.142	(0.091)
2009 gross household income	0.086*	(0.035)
2009 gross household income squared	-0.003*	(0.001)
Own (=1) or Rent (=2) the house	0.117	(0.165)
Total square footage of the house	0.000**	(0.000)
Incentive 2008	-0.050	(0.367)
ACEEE 2008	-0.051	(0.940)
Incentive 2009	0.425	(0.373)
ACEEE 2009	-0.514	(0.915)
AWE 2011	-0.003	(0.007)
Constant	0.036	(0.791)
Variables without proportional odds assumption		
Level 1 vs Level 2-5		
Number of household members	0.144	(0.086)
Education level	0.117*	(0.056)
Level 1-2 vs Level 3-5		
Number of household members	0.394***	(0.066)
Education level	0.025	(0.042)
Level 1-3 vs Level 4-5		
Number of household members	0.560***	(0.054)
Education level	0.078*	(0.036)
Level 1-4 vs Level 5		
Number of household members	0.458***	(0.051)
Education level	-0.043	(0.041)
Observations	1761	

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 3: IV First Stage Estimation Results for the Frequency of Using Dishwasher

Endog. variable: Energy Star Dishwasher Ownership	Coeff.	S.E.
Regional share of Energy Star Dishwasher	0.702***	(0.154)
House in urban area (=1)	-0.045**	(0.017)
Number of years living in the house in 2010	0.021***	(0.005)
Age of dishwasher	-0.058***	(0.014)
Have microwave oven	0.123	(0.079)
Number of stoves	-0.005	(0.025)
Number of separate ovens	0.011	(0.018)
Frequency of cooking hot meals	-0.009	(0.008)
Had home energy audit before	0.022	(0.024)
Have Energy Star clothes washer	0.099***	(0.016)
Have Energy Star frige	0.185***	(0.017)
Averge electricity price in 2009 (dollar/kWh)	0.189*	(0.086)
Householder lives with spouse or partner	0.006	(0.022)
2009 gross household income	0.012	(0.007)
2009 gross household income squared	-0.000	(0.000)
Number of household members	-0.006	(0.006)
Education level	0.007	(0.005)
Own (=1) or Rent (=2) the house	-0.110***	(0.033)
Total square footage of the house	-0.000	(0.000)
ACEEE 2008	-0.068	(0.126)
ACEEE 2009	0.034	(0.116)
AWE 2011	-0.001	(0.001)
Constant	0.060	(0.179)
Observations	1761	
R^2	0.205	

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 4: 2SLS Second Stage Estimation Results for the Frequency of Using Dishwasher

Dependent variable: Frequency of Using Dishwasher	Coeff.	S.E.
Energy Star Dishwasher	-1.409	(0.844)
House in urban area (=1)	-0.185*	(0.077)
Age of house in 2010	-0.001	(0.001)
Number of years living in the house in 2010	0.007	(0.030)
Age of dishwasher	-0.080	(0.076)
Have microwave oven	-0.104	(0.333)
Number of stoves	0.015	(0.106)
Number of separate ovens	0.064	(0.083)
Frequency of cooking hot meals	0.131***	(0.032)
Had home energy audit before	0.124	(0.105)
Have Energy Star clothes washer	0.258*	(0.103)
Have Energy Star frige	0.222	(0.169)
Averge electricity price in 2009 (dollar/kWh)	-0.046	(0.783)
Householder lives with spouse or partner	0.365***	(0.084)
2009 gross household income	0.074**	(0.026)
2009 gross household income squared	-0.002**	(0.001)
Number of household members	0.224***	(0.027)
Education level	0.028	(0.021)
Own (=1) or Rent (=2) the house	-0.132	(0.147)
Total square footage of the house	0.000*	(0.000)
ACEEE 2008	-0.194	(0.531)
ACEEE 2009	0.060	(0.493)
AWE 2011	-0.007	(0.004)
Constant	2.782***	(0.700)
Observations	1761	
R^2	0.032	

Standard errors in parentheses
* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table 5: OLS Estimation of the Reduced Relation between Frequency of Use and Eneregy Star Status

Dependent Variable: Frequency of Using Dishwasher		
	Coeff.	S.E.
House in urban area (=1)	-0.121*	(0.061)
Regional share of Energy Star Dishwashers	-0.989	(0.549)
Age of house in 2010	-0.002	(0.001)
Number of years living in the house in 2010	-0.023	(0.021)
Age of dishwasher	0.002	(0.053)
Have microwave oven	-0.277	(0.266)
Number of stoves	0.022	(0.099)
Number of separate ovens	0.048	(0.078)
Frequency of cooking hot meals	0.144***	(0.029)
Had home energy audit before	0.093	(0.096)
Have Energy Star clothes washer	0.118*	(0.055)
Have Energy Star frige	-0.038	(0.055)
Averge electricity price in 2009 (dollar/kWh)	-0.310	(0.720)
Householder lives with spouse or partner	0.357***	(0.076)
2009 gross household income	0.057**	(0.021)
2009 gross household income squared	-0.002**	(0.001)
Number of household members	0.232***	(0.024)
Education level	0.018	(0.018)
Own (=1) or Rent (=2) the house	0.023	(0.096)
Total square footage of the house	0.000**	(0.000)
ACEEE 2008	-0.097	(0.475)
ACEEE 2009	0.012	(0.439)
AWE 2011	-0.007	(0.004)
Constant	2.699***	(0.596)
Observations	1761	
R^2	0.202	

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

B.3 Full regression tables for Energy Star room air conditioner and its frequency of use

Table 6: OLS Estimation Results for the Frequency of Using Room Air Conditioner

Dependent Variable: Frequency of Using Room Air Conditioner	Coeff.	S.E.
Energy Star Room Air Conditioner	0.140*	(0.070)
House in urban area (=1)	-0.085	(0.077)
Age of house in 2010	-0.001	(0.001)
Number of years living in the house in 2010	-0.019	(0.019)
Housing unit shaded from sun by large trees	-0.027	(0.056)
Had home energy audit before	0.063	(0.108)
Have central air conditioner	-0.114	(0.119)
Number of room air conditioners	0.096**	(0.030)
Age of the most used room air conditioner	0.002	(0.056)
Number of ceiling fans	-0.025	(0.015)
Dehumidifier used	-0.055	(0.079)
Averge electricity price in 2009 (dollar/kWh)	-0.300	(0.841)
Have Energy Star clothes washer	-0.004	(0.064)
Have Energy Star frige	-0.015	(0.058)
ACEEE 2008	0.229	(0.402)
ACEEE 2009	-1.299***	(0.356)
AWE 2011	0.008	(0.005)
Householder is male	-0.121*	(0.054)
2009 gross household income	0.010	(0.018)
2009 gross household income squared	-0.000	(0.001)
Number of household members	-0.027	(0.018)
Education level	-0.037*	(0.018)
Own (=1) or Rent (=2) the house	0.001	(0.064)
Total square footage of the house	-0.000	(0.000)
Total number of rooms in the house	-0.014	(0.021)
Total number of stories in the house	-0.000	(0.004)
Cooling degree days in 2009, base 65F	0.000	(0.000)
Cooling degree days, 1981-2010 average, base 65F	-0.000	(0.000)
AIA Climate Zone	0.077	(0.048)
Constant	2.407***	(0.270)
Observations	907	
R^2	0.144	

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 7: Ordered Logit Estimation Results for the Frequency of Using Room Air Conditioner

Dependent Variable: Frequency of Using Room Air Conditioner		
	Coeff.	S.E.
Energy Star Room Air Conditioner	0.316	(0.177)
House in urban area (=1)	-0.201	(0.188)
Age of house in 2010	-0.002	(0.003)
Housing unit shaded from sun by large trees	-0.077	(0.146)
Had home energy audit before	0.172	(0.311)
Have central air conditioner	-0.099	(0.297)
Number of room air conditioners	0.250**	(0.078)
Age of the most used room air conditioner	0.045	(0.145)
Number of ceiling fans	-0.063	(0.042)
Dehumidifier used	-0.105	(0.219)
Have Energy Star clothes washer	-0.014	(0.167)
Have Energy Star frige	-0.050	(0.150)
ACEEE 2008	1.315	(1.215)
ACEEE 2009	-3.619***	(1.087)
2009 gross household income	0.020	(0.047)
2009 gross household income squared	-0.000	(0.002)
Number of household members	-0.067	(0.048)
Education level	-0.092	(0.049)
Own (=1) or Rent (=2) the house	-0.016	(0.157)
Total square footage of the house	-0.000	(0.000)
Total number of rooms in the house	-0.028	(0.053)
Cooling degree days in 2009, base 65F	0.000	(0.000)
Cooling degree days, 1981-2010 average, base 65F	-0.000	(0.000)
AIA Climate Zone	0.179	(0.123)
Constant	1.145	(0.670)
Variables without proportional odds assumption		
Level 1 vs Level 2-3		
Number of years living in the house in 2010	-0.080	(0.050)
Averge electricity price in 2009 (dollar/kWh)	1.932	(3.226)
AWE 2011	0.008	(0.013)
Level 1-2 vs Level 3		
Number of years living in the house in 2010	-0.018	(0.055)
Averge electricity price in 2009 (dollar/kWh)	-15.387**	(5.645)
AWE 2011	0.026*	(0.013)
Observations	907	

Standard errors in parentheses
* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table 8: IV First Stage Estimation Results for the Frequency of Using Room Air Conditioners

	Endog. variable: Energy Star Room Air Conditioner	
	Coeff.	S.E.
Regional share of Energy Star Room Air Conditioner	0.837***	(0.129)
House in urban area (=1)	-0.065*	(0.030)
Age of house in 2010	0.000	(0.001)
Number of years living in the house in 2010	-0.001	(0.008)
Housing unit shaded from sun by large trees	-0.011	(0.025)
Had home energy audit before	-0.065	(0.059)
Have central air conditioner	0.017	(0.054)
Number of room air conditioners	-0.000	(0.013)
Age of the most used room air conditioner	-0.031	(0.028)
Number of ceiling fans	0.005	(0.007)
Dehumidifier used	-0.048	(0.034)
Averge electricity price in 2009 (dollar/kWh)	-0.372	(0.450)
Have Energy Star clothes washer	0.133***	(0.025)
Have Energy Star frige	0.120***	(0.024)
ACEEE 2008	0.100	(0.188)
ACEEE 2009	-0.060	(0.170)
AWE 2011	-0.000	(0.002)
Householder lives with spouse or partner	0.013	(0.030)
2009 gross household income	0.014	(0.009)
2009 gross household income squared	-0.000	(0.000)
Number of household members	-0.016	(0.009)
Education level	0.021*	(0.008)
Own (=1) or Rent (=2) the house	-0.004	(0.026)
Total square footage of the house	-0.000	(0.000)
Total number of rooms in the house	0.013	(0.009)
Cooling degree days in 2009, base 65F	0.000	(0.000)
Cooling degree days, 1981-2010 average, base 65F	-0.000	(0.000)
AIA Climate Zone	-0.019	(0.022)
Constant	-0.011	(0.161)
Observations	907	
R^2	0.189	

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 9: IV Second Stage Estimation Results for the Frequency of Using Room Air Conditioner

Dependent variable: Frequency of Using Room Air Conditioners	Coeff.	S.E.
Energy Star Room Air Conditioner	0.483	(0.550)
House in urban area (=1)	-0.055	(0.084)
Age of house in 2010	-0.001	(0.001)
Number of years living in the house in 2010	-0.018	(0.018)
Housing unit shaded from sun by large trees	-0.021	(0.057)
Had home energy audit before	0.089	(0.131)
Have central air conditioner	-0.117	(0.123)
Number of room air conditioners	0.096**	(0.030)
Age of the most used room air conditioner	0.042	(0.078)
Number of ceiling fans	-0.025	(0.017)
Dehumidifier used	-0.041	(0.085)
Averge electricity price in 2009 (dollar/kWh)	-0.331	(1.276)
Have Energy Star clothes washer	-0.043	(0.095)
Have Energy Star frige	-0.065	(0.095)
ACEEE 2008	0.237	(0.446)
ACEEE 2009	-1.380***	(0.406)
AWE 2011	0.009	(0.005)
Householder lives with spouse or partner	-0.055	(0.062)
2009 gross household income	0.003	(0.020)
2009 gross household income squared	0.000	(0.001)
Number of household members	-0.014	(0.021)
Education level	-0.043*	(0.022)
Own (=1) or Rent (=2) the house	0.007	(0.058)
Total square footage of the house	-0.000	(0.000)
Total number of rooms in the house	-0.021	(0.023)
Cooling degree days in 2009, base 65F	0.000	(0.000)
Cooling degree days, 1981-2010 average, base 65F	-0.000	(0.000)
AIA Climate Zone	0.080	(0.050)
Constant	2.010***	(0.451)
Observations	907	
R^2	0.115	

Standard errors in parentheses
* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table 10: OLS Estimation of the Reduced Relation between Frequency of Use and Regional Uptake of Energy Star

Endog. variable: Energy Star Room Air Conditioner	Coeff.	S.E.
Regional share of Energy Star Room Air Conditioner	-0.079	(0.272)
House in urban area (=1)	-0.086	(0.077)
Age of house in 2010	-0.001	(0.001)
Number of years living in the house in 2010	-0.017	(0.019)
Housing unit shaded from sun by large trees	-0.033	(0.056)
Had home energy audit before	0.061	(0.109)
Have central air conditioner	-0.103	(0.120)
Number of room air conditioners	0.100**	(0.030)
Age of the most used room air conditioner	-0.016	(0.060)
Number of ceiling fans	-0.022	(0.015)
Dehumidifier used	-0.058	(0.078)
Averge electricity price in 2009 (dollar/kWh)	-0.144	(0.823)
Have Energy Star clothes washer	0.021	(0.064)
own_esdishw	-0.047	(0.074)
Have Energy Star frige	0.010	(0.060)
ACEEE 2008	0.194	(0.406)
ACEEE 2009	-1.271***	(0.364)
AWE 2011	0.009	(0.005)
2009 gross household income	0.009	(0.018)
2009 gross household income squared	-0.000	(0.001)
Number of household members	-0.025	(0.018)
Education level	-0.031	(0.018)
Own (=1) or Rent (=2) the house	0.009	(0.062)
Total square footage of the house	-0.000	(0.000)
Total number of rooms in the house	-0.013	(0.021)
Cooling degree days in 2009, base 65F	0.000	(0.000)
Cooling degree days, 1981-2010 average, base 65F	-0.000	(0.000)
AIA Climate Zone	0.065	(0.049)
Constant	2.398***	(0.345)
Observations	907	
R^2	0.136	

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

B.4 Full regression tables for Energy Star dishwasher and electricity consumption

Table 11: OLS Estimation Results for Annual Electricity Consumption

Dependent Variable: Electricity Consumption	Coeff.	S.E.
Energy Star Dishwasher	-405.995	(222.908)
House in urban area (=1)	-1196.121***	(197.820)
Single family house	892.005***	(220.226)
Age of house in 2010	7.521*	(3.383)
Number of years living in the house in 2010	123.304*	(58.409)
Age of dishwasher	-28.538	(144.172)
Have microwave oven	1493.239***	(400.466)
Number of stoves	-20.099	(300.290)
Number of separate ovens	439.779	(239.020)
Frequency of cooking hot meals	102.145	(66.331)
Had home energy audit before	242.057	(278.026)
Have Energy Star clothes washer	312.975	(169.584)
Age of clothes washer	0.524	(5.781)
Have Energy Star frige	785.870***	(160.714)
Having clothes dryer	1325.935***	(246.638)
Averge electricity price in 2009 (dollar/kWh)	-3287.349*	(1348.068)
Receive retirement income	-299.999	(176.447)
Householder lives with spouse or partner	109.013	(178.047)
Householder is male	186.525	(143.347)
2009 gross household income	-4.158	(64.743)
2009 gross household income squared	0.957	(2.057)
Number of household members	684.466***	(68.240)
Education level	-166.458***	(48.758)
Own (=1) or Rent (=2) the house	247.479	(230.571)
Total square footage of the house	0.173*	(0.070)
ACEEE 2008	1842.730	(1272.276)
ACEEE 2009	-584.114	(1130.843)
AWE 2011	-75.197***	(12.982)
Electricity usage for space heating (kWh)	0.391***	(0.066)
Electricity usage for space cooling (kWh)	0.346***	(0.046)
Electricity usage for water heating (kWh)	0.160*	(0.068)
Electricity usage for refrigeration (kWh)	2.415***	(0.128)
Constant	-2054.007*	(972.466)
Observations	1761	
R^2	0.629	

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 12: IV Estimation Results for the Impact of Energy Star Dishwashers on Electricity Consumption

Dependent Variable: electricity consumption, excluding space heating and cooling, water heating and refrigeration.	Coeff.	S.E.
Energy Star Dishwasher	-3586.457	(2082.676)
House in urban area (=1)	-1347.554***	(213.717)
Single family house	1087.198**	(331.728)
Age of house in 2010	6.985*	(3.535)
Number of years living in the house in 2010	204.871*	(80.355)
Age of dishwasher	-193.986	(188.063)
Have microwave oven	1869.584**	(694.434)
Number of stoves	-31.479	(290.780)
Number of separate ovens	474.532*	(218.163)
Frequency of cooking hot meals	82.755	(74.755)
Receive retirement income	-489.752*	(224.297)
Had home energy audit before	305.420	(291.794)
Have Energy Star clothes washer	616.438*	(258.560)
Have Energy Star frige	1371.830**	(418.946)
Having clothes dryer	1421.412**	(457.457)
Averge electricity price in 2009 (dollar/kWh)	-2543.138	(1484.036)
Householder lives with spouse or partner	142.534	(202.792)
2009 gross household income	33.520	(68.700)
2009 gross household income squared	0.149	(2.124)
Number of household members	637.524***	(69.604)
Education level	-142.768**	(52.374)
Own (=1) or Rent (=2) the house	-72.930	(339.434)
Total square footage of the house	0.159**	(0.060)
Electricity usage for space heating (kWh)	0.361***	(0.058)
Electricity usage for space cooling (kWh)	0.346***	(0.029)
Electricity usage for water heating (kWh)	0.183**	(0.059)
Electricity usage for refrigeration (kWh)	2.424***	(0.102)
ACEEE 2008	1785.024	(1382.868)
ACEEE 2009	-305.824	(1267.332)
AWE 2011	-79.647***	(12.220)
Constant	43.976	(1665.473)
Observations	1761	
R^2	0.588	

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

B.5 Full regression tables for Energy Star Air Conditioner and electricity consumption

Table 13: OLS Estimation Results for Annual Electricity Consumption for Space Cooling

Dependent Variable: Electricity Consumption for Space Cooling	Coeff.	S.E.
Energy Star Room Air Conditioner	212.395*	(92.537)
House in urban area (=1)	-149.174	(96.081)
Age of house in 2010	-3.709*	(1.551)
Number of years living in the house in 2010	-52.424*	(24.628)
Housing unit shaded from sun by large trees	67.611	(72.118)
Had home energy audit before	365.493*	(165.199)
Number of room air conditioners	317.497***	(37.124)
Age of the most used room air conditioner	74.287	(73.088)
Number of ceiling fans	23.974	(21.438)
Dehumidifier used	-122.240	(108.173)
Household received retirement income	-15.896	(87.016)
Averge electricity price in 2009 (dollar/kWh)	-1988.850	(1657.188)
Have Energy Star clothes washer	-2.274	(80.699)
Have Energy Star frige	-3.435	(74.582)
ACEEE 2008	-239.087	(578.997)
ACEEE 2009	-1480.877**	(514.555)
AWE 2011	22.824***	(6.504)
Householder lives with spouse or partner	-35.144	(80.262)
2009 gross household income	25.047	(23.700)
2009 gross household income squared	-1.067	(0.834)
Number of household members	-13.383	(25.131)
Education level	-6.791	(24.016)
Own (=1) or Rent (=2) the house	-49.876	(75.028)
Total square footage of the house	0.111*	(0.045)
Total number of rooms in the house	12.956	(28.159)
Cooling degree days in 2009, base 65F	0.379	(0.195)
Cooling degree days, 1981-2010 average, base 65F	0.109	(0.203)
AIA Climate Zone	245.700***	(59.514)
Constant	-376.082	(319.029)
Observations	907	
R^2	0.536	

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 14: IV Estimation Results for Annual Electricity Consumption for Space Cooling

Dependent variable: Electricity Consumption from Space Cooling	Coeff.	S.E.
Energy Star Room Air Conditioner	301.867	(652.243)
House in urban area (=1)	-162.412	(99.423)
Age of house in 2010	-2.436	(1.462)
Number of years living in the house in 2010	-35.240	(22.452)
Housing unit shaded from sun by large trees	89.565	(67.755)
Had home energy audit before	296.195	(155.600)
Have central air conditioner	1784.454***	(145.325)
Number of room air conditioners	412.434***	(35.036)
Age of the most used room air conditioner	86.392	(92.821)
Number of ceiling fans	-19.568	(20.053)
Dehumidifier used	-174.617	(100.712)
Household received retirement income	-53.204	(80.047)
Averge electricity price in 2009 (dollar/kWh)	-2202.439	(1510.571)
Have Energy Star clothes washer	27.756	(113.635)
Have Energy Star frige	-23.418	(112.444)
ACEEE 2008	-476.993	(527.879)
ACEEE 2009	-1006.070*	(481.599)
AWE 2011	22.025***	(5.918)
Householder lives with spouse or partner	-128.223	(74.325)
2009 gross household income	8.713	(23.548)
2009 gross household income squared	-0.599	(0.811)
Number of household members	-2.080	(24.625)
Education level	-11.604	(25.830)
Own (=1) or Rent (=2) the house	-66.057	(68.385)
Total square footage of the house	0.069	(0.041)
Total number of rooms in the house	-15.560	(27.506)
Cooling degree days in 2009, base 65F	0.537**	(0.180)
Cooling degree days, 1981-2010 average, base 65F	-0.023	(0.186)
AIA Climate Zone	167.349**	(59.781)
Constant	-276.455	(532.590)
Observations	907	
R^2	0.603	

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

B.6 OLS regression for incentive and ACEEE policy scores and Energy Star ownership

Table 15: OLS Estimation Results for Policy Scores and Having Energy Star Dishwasher

Dependent variable: Dishwasher is Energy Star		
	Coeff.	S.E.
Incentive 2008	0.092	(0.057)
Incentive 2009	-0.011	(0.056)
ACEEE 2008	-0.051	(0.142)
ACEEE 2009	0.076	(0.138)
AWE 2011	-0.001	(0.001)
House in urban area (=1)	-0.045**	(0.017)
Age of house in 2010	-0.000	(0.000)
Number of years living in the house in 2010	0.021***	(0.005)
Age of dishwasher	-0.057***	(0.014)
Have microwave oven	0.127	(0.078)
Number of stoves	-0.002	(0.025)
Number of separate ovens	0.010	(0.018)
Frequency of cooking hot meals	-0.007	(0.008)
Had home energy audit before	0.024	(0.025)
Have Energy Star clothes washer	0.101***	(0.016)
Have Energy Star frige	0.186***	(0.017)
Averge electricity price in 2009 (dollar/kWh)	0.231**	(0.085)
Householder lives with spouse or partner	0.004	(0.022)
2009 gross household income	0.013	(0.007)
2009 gross household income squared	-0.000	(0.000)
Number of household members	-0.007	(0.006)
Education level	0.008	(0.005)
Own (=1) or Rent (=2) the house	-0.120***	(0.033)
Total square footage of the house	-0.000	(0.000)
Constant	0.621***	(0.124)
Observations	1761	
R^2	0.196	

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 16: OLS Estimation Results for Policy Scores and Having Energy Star Room Air Conditioner

Dependent variable: Most Used Room AC is Energy Star	Coeff.	S.E.
Incentive 2008	0.098	(0.151)
Incentive 2009	0.004	(0.128)
ACEEE 2008	-0.030	(0.202)
ACEEE 2009	0.131	(0.203)
AWE 2011	0.000	(0.003)
House in urban area (=1)	-0.074*	(0.031)
Age of house in 2010	0.001	(0.001)
Number of years living in the house in 2010	0.002	(0.008)
Housing unit shaded from sun by large trees	-0.023	(0.026)
Had home energy audit before	-0.061	(0.058)
Have central air conditioner	0.037	(0.055)
Number of room air conditioners	0.007	(0.014)
Age of the most used room air conditioner	-0.100***	(0.025)
Number of ceiling fans	0.005	(0.007)
Dehumidifier used	-0.029	(0.035)
Averge electricity price in 2009 (dollar/kWh)	0.119	(0.343)
Have Energy Star clothes washer	0.134***	(0.025)
Have Energy Star frige	0.139***	(0.025)
2009 gross household income	0.014	(0.009)
2009 gross household income squared	-0.000	(0.000)
Number of household members	-0.013	(0.008)
Education level	0.021*	(0.009)
Own (=1) or Rent (=2) the house	0.006	(0.027)
Total square footage of the house	-0.000	(0.000)
Total number of rooms in the house	0.016	(0.009)
Cooling degree days in 2009, base 65F	0.000	(0.000)
Cooling degree days, 1981-2010 average, base 65F	-0.000	(0.000)
AIA Climate Zone	-0.041	(0.023)
Constant	0.684***	(0.115)
Observations	907	
R^2	0.150	

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001