# Free Riding, Upsizing, and Energy Efficiency Incentives in Maryland Homes

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**ABSTRACT**

We use a unique dataset that combines an original survey of households, information about the structural characteristics of their homes, utility-provided electricity usage records and program participation status, to study the uptake of energy efficiency incentives and their effect on residential electricity consumption. Attention is restricted to homes where heating and cooling is provided exclusively by air-source heat pumps. We deploy a difference-in-difference study design and find that replacing a heat pump with a new one does reduce electricity usage by 8% on average. The effect differs dramatically across households based upon whether they receive an incentive towards the purchase of a new heat pump. Among incentive recipients, the effect is small, and the larger the incentive, the smaller the reduction in electricity usage. These findings suggest that capital costs are incorporated into the (long-term) cost of energy, generating an apparent rebound effect that is much more pronounced for incentive recipients.

**Keywords:** Energy Efficiency, Household Behavior, Energy Efficiency Incentives, Electricity Usage, Rebound Effect, Free Rider

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## 1. INTRODUCTION

Residential energy efficiency policies in the US and several other countries have traditionally relied on standards for equipment and new home construction, on incentives, and, more recently, on the explicit provision of information about the energy efficiency of devices and buildings.[1] These approaches have received much recent attention due to i) the large contribution of buildings to total energy use (30–40%) and the associated carbon dioxide ($CO_2$) emissions, ii) assessments that improving energy efficiency in buildings would reduce carbon emissions at low or even negative cost (Levine et al. 2007; Choi Granade et al., 2009), and iii) the view that homeowners are reluctant to invest in energy efficiency improvements.[2]

1. See www.muredatabase.org (last accessed 20 November 2013).
2. Debate continues as to whether an "energy efficiency gap" truly exists and what its causes are (Jaffe and Stavins, 1994; Hassett and Metcalf, 1993; Golove and Eto, 1996; Allcott and Greenstone, 2012). See Gillingham and Palmer (2013) for a recent discussion.

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Incentives usually take the form of tax credits or direct rebates to the consumers who install insulation or energy-saving windows, and/or purchase high-efficiency heating systems, air conditioners, water heaters, and appliances. Between 2005 and 2009, federal expenditure on residential energy efficiency programs was \$2.2 billion (2009 \$) (Allaire and Brown, 2012), and in fiscal year 2013 federal expenditures on tax preferences targeting energy efficiency improvements in existing and new homes reached almost \$4 billion (2013 \$) (Dinan, 2013).

Proper assessment of the effectiveness of incentive programs is inherently problematic because of adverse selection (people are replacing equipment at the end of life; Sandler, 2012) and the likelihood that the programs attract people who are systematically (and unobservably) more motivated or productive at reducing usage. These considerations have led observers to conclude that, unless the presence of "free riders"—persons who pocket the incentive, but would have done the energy-efficiency renovation or upgrade anyway—is adequately accounted for, assessments will generally overstate the cost-effectiveness of the programs, i.e., the cost per unit of energy or carbon emissions saved (Joskow and Marron, 1992; Hartman, 1988; Waldman and Ozog, 1996; Malm, 1996; Grosche and Vance, 2009; Allaire and Brown, 2012).

Other undesirable behavioral responses are possible. For example, using data from Canada, Young (2008) documents that many households do not dispose of old and inefficient refrigerators, once they replace them with new ones, and keep using them as "beer fridges" (to store cold beverages), for a net increase in electricity consumption. This can be avoided with careful incentive program design, which in turn will increase program complexity and the associated administrative and enforcement costs. Similarly, in programs that seek to replace conventionally-generated electricity with electricity generated from renewables, Jacobsen et al. (2009) find that participating households actually increased electricity usage, despite the fact that the price per kWh is higher than that of conventionally generated power.

One concern is that high-efficiency equipment lowers the price per unit of energy services, engendering a combination of substitution and income effects known as the rebound effect (Dimitropolous and Sorrell, 2007), with households purchasing more energy services and/or energy than before. Very strong rebound effects diminish the attractiveness of energy efficiency incentive programs, but in the case of residential electricity and heating fuel use, the (direct) rebound effects have generally been thought to be small (Sorrell et al., 2009; Linares and Labandeira, 2010; Gillingham et al., 2013).[3]

These claims are often based on inferring the extent of the rebound effect from energy price elasticities (Gillingham et al., 2013). Past evaluations often relied on engineering estimates of the energy savings from certain technologies or measures, without observing actual behaviors, and as such, depending on study design and implementation specifics, may have either over- or understated the true energy savings (Jacobsen and Kotchen, 2013; Grosche, Schmidt and Vance, 2012; Greening et al., 2000; Sorrell et al., 2009; Metcalf and Hassett, 1999). There is also disagreement in the literature as to what exactly should be measured—physical energy units (e.g., kWh), energy services (the temperature in a home over a specified period), or other units yet (Turner, 2013).

Empirical work on incentive programs and their effects on energy use is, however, no easy task. In the handful of US government-conducted surveys about residential energy use and energy-efficiency investments, renovations are not described in sufficient detail and information about energy-efficiency incentives is limited or absent altogether. Some authors use electricity or gas

3. Frondel and Vance (2013) document large effects among German drivers following motor fuel price changes.

consumption records provided by the utilities to examine responsiveness to shocks (such as price changes or the provision of feedback on consumption, e.g. Allcott, 2011), but these studies usually lack information about the dwelling and energy efficiency upgrades, which are ignored or assumed away.

To circumvent these limitations in the literature, we designed and implemented our own survey of households and have carefully attempted to address each data weakness (or omission) mentioned above in the construction of the sample. We conducted our survey in four counties in Maryland in the last quarter of 2011. In the five years prior to the survey, Maryland residents had plentiful opportunities to avail themselves of energy-efficiency incentives. In addition to the incentives made available by the Energy Policy Act (2005) and the American Reinvestment and Recovery Act of 2009, Maryland residents received state- and utility-offered incentives in 2010 and 2011.

The survey questionnaire asked owners of single-family homes whether in the last five years they had 1) replaced the heating system, 2) replaced the air conditioning system, and 3) installed wall or attic insulation, new windows, etc. If so, we further asked them how much they spent on each of these renovations or installations, whether they received a rebate or tax credit on the purchase, how much that rebate or tax credit was for, and whether they would have still done the replacement(s) or installation(s), had the rebate or tax credit been absent altogether.

We sent letters to 10,000 Maryland households who own the homes they live in. A total of 1153 of them filled out our questionnaire in September-December 2011. We conducted follow-ups of subsamples of participants and non-participants in the summer of 2012.

A unique aspect of our study is that for all of the 10,000 households that were invited to participate in the survey, we have extensive information about the dwelling and its structural characteristics. Additional information about the characteristics of housing and residents in the neighborhood comes from the Census. We also have these households' monthly electricity usage and billing records (provided by the local utility) from December 2007 to April 2012, and information about participation in utility programs.

These sources of data allow us to create a unique panel dataset that we use to study equipment replacement, uptake of incentives, and their effect on energy use. We ask three key research questions. First, in a setting where energy efficiency standards are present, does replacing the heating/cooling system with a new and (at least on paper) more energy-efficient system truly reduce energy use? Second, is there heterogeneity in the effect of changing the heating and cooling equipment? If so, what are the main drivers of this heterogeneity? Third, do households who apply for and receive incentives reduce their electricity consumption more, either because they are more "productive" at reducing usage (Joskow and Marron, 1992) or because they are required to purchase more energy-efficient equipment?

In this paper attention is focused on homes heated and cooled by a single device, a heat pump. Heat pumps are common in our study area, which is not served by the natural gas line network, where they are the principal heating and cooling system for some 50% of the homes. We study heat pump *replacements*. The 2005 Energy Policy Act required that as of 2006 all new heat pumps meet certain energy efficiency standards, which means that households that replaced their heat pumps in the five years prior to the survey must have adopted more energy-efficient equipment.

We use a difference-in-difference approach where the treatment group is comprised of those who changed their heat pumps within the last five years, the control group is comprised of those who haven't, and the treatment is defined as the replacement of a heat pump. We further examine if the treatment effect on electricity usage depends on household and house characteristics, is different for households who received an incentive for their purchase, and depends on the incentive amount. We investigate heterogeneity and incentive effects with fixed-effects "within" estimation and fixed-effects quantile regressions.

Briefly, we find that replacing an existing heat pump with a new one reduces electricity usage, after we control for household-specific fixed effects, weather and time of the year. The average treatment effect on the treated is an 8% reduction. There is a large difference, however, between "natural replacers" (those that replace units without incentives) and incentive recipients—and the difference is the opposite of what we expected. The former reduce their electricity usage by about 16%; for the latter the reduction is virtually nil, despite the fact that the manufacturer-specified energy efficiency ratings and the expenditure on the new heat pump is virtually identical across the two groups of replacers.

We also find that the larger the rebate, the *less* the electricity reduction. For all practical purposes, rebates of $1000 or more have no effect on usage. Rebates of $300 and $450 (the typical rebates offered by utility or state programs) result in usage reduction of 6.22% and 5.5% respectively.

The apparent rebound effect documented in our study, and the fact that it so extreme among those households that received incentives, suggest that households do include equipment expenditures into the calculation of the cost per unit of energy services, a matter where previous literature on the rebound effect is unclear (see Turner, 2013). Another possible explanation for this extreme rebound effect, based on evidence suggested by the survey responses, is that the "rebaters" were disproportionately replacing "inadequate" units, using the rebates to defray the cost of more powerful units, or of units that end up being used more. This is consistent with evidence from the quantile regressions that households with low usage had smaller usage reductions or even increased their usage.

## 2. BACKGROUND: ENERGY EFFICIENCY INCENTIVES AND STANDARDS FOR HEAT PUMPS

In the five years before the main survey of this paper, Maryland residents had ample opportunities to avail themselves of subsidies for replacing their heat pumps with more energy-efficient ones. Funding came from the federal government (in the form of tax credits) and Maryland utilities participating in the State's EmPower Program (in the form of rebates).

The 2005 Energy Policy Act established tax credits for 10% of the cost, with a cap of $500. These tax credits were to expire at the end of 2008. The Energy Policy Act also established energy efficiency standards for heat pumps manufactured in and after 2006. For example, they must meet a minimum Seasonally-Adjusted Energy Efficiency Rating (SEER) of 13.[4]

In February 2009, the American Recovery and Reinvestment Act (the stimulus package) re-instated the tax credits, increasing them to 30% of cost, up to a maximum of $1500. The tax

4. The SEER is a measure of the efficiency of a cooling unit designed to be representative of how the system performs over the entire cooling season where the outdoor temperature varies. It is calculated as the ratio of cooling output energy over a season over the input of electrical energy over a season. The Heating Seasonal Performance Factor (HSPF) is the heating analog of the SEER: It measures the representative heater efficiency over a season. In practice, both the SEER and HSPF are measured from a test protocol that varies indoor and outdoor temperatures, and considers compressor type (e.g. single stage, variable), as specified under ANSI/AHRI standard 210/240.
In both cases, a higher rating denotes a more efficient unit that uses less energy to heat or cool. For heat pumps, HPSF and SEER are very highly correlated.

credits were extended to the end of 2010. Many of the tax credits subsequently continued to be renewed until the end of 2013.

In 2008, the State of Maryland established the EmPower Program, with the goal of reducing energy consumption by 15% by 2015.[5] Participating electric and gas utilities established a number of initiatives to help meet this goal, including—starting in January 2010—rebates of $200 and $400 on the purchase of air-source heat pumps in tier I and tier II, respectively. This rebate structure remained in place for all of 2010 and 2011. In January 2012, they were revised to $200 and $300 respectively, a rebate of $500 was established for Tier III air-source heat pumps, and a rebate of $300 was offered for ductless mini-split heat pumps (an option that requires much less pipe- and ductwork) that met specified efficiency requirements.[6] The electric utility serving our study area was one of the participants in the EmPower rebate program.

## 3. STUDY DESIGN AND DATA SOURCES

### *A. Survey Questionnaire*

Our survey questionnaire gathered information about energy use at home, including usage in kWh per month, average bill amount, heating and cooling equipment, fuels, and attitudes towards conservation and energy efficiency. We also asked respondents whether in the last five years they had 1) replaced the heating system, 2) replaced the central air conditioning system or window units (air conditioning is an important driver of electricity usage in the summer in the mid-Atlantic region of the US), and 3) installed wall or attic insulation, new windows, or various other energy-saving purchases.

If so, we further asked them how much they spent on these items, whether they received a rebate or tax credit on this purchase, how much that rebate or tax credit was for, and which entities provided it (e,g, federal government, state, etc.). Finally, we asked respondents whether they would have still done those replacements or installations, had the rebate or tax credit been absent altogether.

### *B. Universe and Sample*

To develop our main sample, we combined several sources of data. The first is MDPropertyView (MDPV), a database that documents all properties in Maryland and is compiled by the State of Maryland using data from each county. For each dwelling MDPV lists the premise address, name and address of the owner, and structural characteristics (e.g., size, single-family or attached home, vintage, construction quality, construction materials, heating and cooling equipment, etc.). The records are updated annually with any new sale(s) and modifications in size or structure. We used MDPV to create our universe for the purpose of the survey, namely single-family homes or townhouses built in 1940–2000 with the owners living on the premises.

We partitioned this universe into four groups. Since January 2010, the local electrical utility has been offering rebates on the purchase of high-efficiency HVAC equipment, in part to meet its obligations as per the EmPower Maryland program. Our first group is thus comprised of program

5. See http://energy.maryland.gov/home.html (last accessed 20 November 2013).

6. Tier I air source heat pumps have at least 14.5 SEER and 12 EER and 8.2 HSPF. Tier II air-source heat pumps have at least 15 SEER and 12.5 EER and 8.5 HSPF. Tier III air-source heat pumps have at least 16 SEER and 13 EER and 9 HSPF. A ductless mini-split heat pump must meet the same requirements as a Tier III air-source heat pump to qualify for the $300 rebate. See http://energy.maryland.gov/facts/empower.html (last accessed 25 November 2013).

**Table 1: Summary of Original Sampling Plan (addressees of letters with invitation to participate in the survey) and Survey Response**

| | Letters sent N | Survey participants N |
|---|---|---|
| Homes built 1940–2000 | 6846 | 724 |
| participants in utility rebate and audit programs, homes built 1940–2000 | 1143 | 221 |
| recent movers (Jan-Jun 2011), homes built 1940–2000 | 1171 | 82 |
| renovators (building permit filed 2007–2011, homes built 1940–2000) | 840 | 126 |
| total | 10000 | 1153 |

participants (as of April 2011, based on proprietary information from the utility) who lived in pre-2000 single-family homes or townhouses. We include all these homes/households (N = 1143) in our sample.

Our second group is comprised of pre-2000 homes with households that moved into these homes in January-June 2011 (we purchased this list from a commercial vendor), and our third group is comprised of pre-2000 homes for which a building permit was filed with the county in 2007–2011. We include all these homes in our sample under the assumption that recent movers and recent renovators (which come to a total of N = 2011) may be more likely to undertake energy-efficiency upgrades in their homes. Our fourth group is comprised of the remainder of the universe, and includes some 60,000 homes. We drew a random sample of 6846 addresses from group 4.

In sum, our universe of candidate sampling units were single-family homes and townhomes built before 2000 and occupied by their owners. Our sampling frame is a mix of stratified and choice-based sampling (see table 1), which means that it is necessary to calculate and use appropriate weights when extrapolating sample statistics to the population.[7] The combined sample was comprised of a total of 10,000 households whom we invited to participate in our survey.

### *C. Survey Administration*

We sent letters to the households living in the sample of 10,000 households described above (see table 1), asking prospective respondents to visit a dedicated website and complete the questionnaire. A user name and password were provided to each addressee.

The letters were evenly divided into two waves. The first was mailed in early September 2011, and the second in October 2011. Each mailing was followed by a reminder letter a week later. The survey was closed on January 4, 2012. We received a total of 1153 completed questionnaires, which we refer to as our "main survey" sample, and 44 letters were returned to us by the US Postal Service as undeliverable, for a response rate of 1153/9956 = 11.58%.[8]

7. The weights adjust our samples shares to the population shares. We use the ECSML weights described in Manski and Lerner (1977), where the ECSML weight $w_j$ for an observation in stratum $j$ is equal to $Q_j/H_j$, with $Q_j$ the population share in stratum $j$ and $H_j$ the sample share in stratum $j$. Manski and Lerner (1977) show that the maximum likelihood estimates based on the weighted log likelihood function are consistent for the true coefficients.

8. This response rate is within the range typically observed with mail invitations sent to a general population and web-based questionnaires (see, for example. Kaplowitz et al., 2009; Ramseier, 2013). We examine issues of self-selection into the survey in section 5.B.

We conducted follow-ups on subsamples of non-participants (Phase I) and participants (Phase II) in the summer of 2012. Specifically, in the Phase I follow up we drew a random sample of 500 households that had received the survey invitation letters back in 2011, but had not filled out the questionnaire. We tracked down phone numbers for 429, spoke over the phone to 61 of them, and administered them an abbreviated version of the on-line questionnaire.

As part of the Phase II survey, we re-contacted all of the 413 households who in the main survey had reported changing their heating system—heat pump or other—within the previous 5 years. We spoke to 104 of them over the phone, and gathered additional information about equipment, subsidies, and related decisions.

*D. Data Available for Analysis*

For all of the 10,000 households who were invited to participate in the main survey—whether or not they actually participated—we have extensive information about the dwelling and its structural characteristics from MDPV, plus housing stock and resident characteristics at the census block group from the Census. We also have these households' monthly electricity meter readings and bills (provided by the local utility) from December 2007 to April 2012, as well as the heating degree days (HDDs) and cooling degree days (CDDs) for each billing period.[9] We thus have a panel dataset, with up to 54 electricity meter readings per household, weather information, and ample details about the dwelling.

Household energy-using equipment, expenses, recent replacements, rebate uptake and energy-efficiency upgrade decisions are available for 1153 of these households—namely for the participants in the main survey. In this paper, we study the subset of households from this sample of 1153 who use exclusively heat pumps for both heating and cooling.

Attention is restricted to heat pumps for three reasons.[10] First, they provide heating in the winter and cooling in the summer, and so households with heat pumps (almost) exclusively use only one type of energy—electricity—for which we have monthly consumption levels for the last five years. Households with heat pumps tend to be heavy users of electricity.[11] Second, regulatory

9. We matched each day of each billing period with the Global Surface Summary of the Day records from the Patuxent Air Naval Station (the weather monitoring station closest to our study area) from the National Climatic Data Center within the National Oceanographic and Atmospheric Agency, and computed HDDs and CDDs for each billing period for each respondent using a reference temperature of 65° F (about 18° C). Variation in HDD and CDD across respondents and over time comes from the fact that billing periods start and end on different days for different households.

10. By heat pump, we mean a traditional air-source heat pump or a ductless mini-split heat pump. Ground-source (geothermal) heat pumps are excluded from this analysis for four reasons. First, there are only 26 households with geothermal heat pumps in our sample. Second, installing them for the first time in a home may actually increase electricity usage while decreasing gas and heating oil usage. Third, all of the 26 households that installed a geothermal heat pump in the five years prior to the main survey of this paper received incentives. Fourth, the cost of geothermal systems is much higher than that of air-source or ductless mini-split heat pumps, and so are the relevant tax credits and rebates.

11. Using monthly usage records over 5 years from a total of 17,000 single-family homes and townhouses in the same area as the sample used in this paper, we estimate that in the winter months (November through April) homes with electric heat pumps use approximately 38% more electricity than otherwise comparable homes that are heated with heating oil, gas, or other fuels. In the summer months, homes with heat pumps use approximately 10% more electricity than their counterparts without heat pumps. These effects are estimated through regressions that control for house size, weather, length of the billing period, and type of heat. The difference in electricity consumption is 20% over the entire year. This annual difference is similar to that from a simple comparison of (unconditional) median consumption per billing period, which is 1411 kWh for homes served by heat pumps, and 1131 for homes served by non-electric heating systems. For an additional comparison, calculations by Puget Sound Energy indicate that in the Pacific Northwest, in an area with about 10% more heating degree days than Maryland (4400 a year versus Maryland's 4000), but a negligible number of cooling degree days (390 a year

standards have resulted in rapid and dramatic improvements in the energy efficiency of these devices over the last few years, implying that replacing an older unit with a new one should reduce electricity usage, *ceteris paribus*, even when the old one is only 5–6 years old (Portland General Electric, 2013).[12] Third, heat pumps are a common device in the study area, which does not have access to the natural gas network. Data from MDPV indicate that over 60% of the pre-2000 single-family homes in our study region use heat pumps.

## 4. THE MODEL

### *A. Theoretical Considerations*

Decisions about energy-using capital and energy usage are usually represented assuming a two-stage utility maximization process. In the first stage, the household chooses the level of consumption of other goods and the desired level of "energy services" (e.g., thermal comfort). In the second stage, the household chooses the combination of capital stock $K$ and energy use $E$ that minimizes expenditure for any given level of energy services. At the optimum, the slope of the isoquant representing the possible combinations of capital and energy for any given technology is equal to the ratio of capital and energy prices.

Energy-efficient technologies are represented in this framework by a new set of isoquants where, for any level of capital, a given level of thermal comfort is attained with less energy usage than under the older technology. If more efficient equipment is more expensive, however, the household may substitute energy for capital, and, depending on prices and substitution possibilities, may even end up using more energy than before.

Tax credits that are proportional to the cost of capital tend counter this effect, since they lower the cost per unit of capital. Lump-sum incentives, such as rebates, are an income transfer to the household. Depending on preferences, income, prices, and technologies, a household that changes equipment in the presence of efficiency standards and incentives may end up at higher or lower energy consumption than before.

Whether or not incentives are present, better energy efficiency reduces the price per unit of energy service, and may engender a combination of substitution and income effects known as the rebound effect (Dimitropolous and Sorrell, 2007), with households purchasing more energy services than before. There is considerable debate in the literature and in policy circles as to the extent of the rebound effect (see Turner, 2013, and Gillingham et al., 2013, for recent discussions), which may vary across settings and energy user types, and whether it should be measured by comparing energy use or energy services before and after equipment changes (or energy price changes). Expert judgment and evidence from earlier studies suggests that it is likely to be small in the case of residential electricity and heating.[13]

versus Maryland's 1400), the average home served by an energy-efficient heat pump can be expected to use 7200–7500 kWh a year just for the heat pump (see https://pse.com/savingsandenergycenter/GetReEnergized/Documents/4343_EnergyCostGuide.pdf, last accessed 28 February 2014). The average annual electricity consumption for a home in the Pacific Northwest is about 12000 kWh (see http://www.eia.gov/tools/faqs/faq.cfm?id = 97&t = 3).

12. See http://www.portlandgeneral.com/residential/energy_savings/getting_started/energy_cost_calculator.aspx (last accessed 28 February 2014).

13. Greening et al. (2000) notes that many early studies may have overstated the rebound effect because of their reliance on engineering-predicted energy savings, and that others simply did not meet minimum study quality criteria or did not account for changing equipment, etc. They also note that the rebound effect will depend on the level of awareness that consumers during energy service consumption. For example, consumers are aware of the ambient temperature, thermal

*B. Econometric Model*

One major goal of this paper is to examine household energy consumption when existing equipment is replaced with a newer, and more energy efficient, device. We use a panel-data version of the difference-in-difference approach. The "treatment" is the replacement of a heat pump with a new one during the last five years and the estimation sample is comprised of observations from this treatment group and observations from a control group (households who have a heat pump, but did not replace it in the last five years).[14] We have monthly electricity usage records spanning December 2007 to April 2012.

The model is

$$lnE_{it} = \alpha_i + \beta lnDDays_{it} + \gamma(lnDDays_{it} \times Winter_{it}) + \boldsymbol{M_{it}\delta} + \lambda \cdot HEATTREAT_{it} + \varepsilon_{it} \qquad (1)$$

where $i$ denotes the household, t the billing period, $E$ is the electricity usage in kWh in billing period t, *DDays* is the sum of heating degree days and cooling degree days during that billing period, Winter is a dummy denoting the winter months, $\boldsymbol{M}$ is a set of month-by-year dummies,[15] $\boldsymbol{\delta}$ is the vector of associated effects, and *HEATTREAT* is a dummy that takes on a value of one when the new heating pump is installed.

We are especially interested in λ, the average treatment effect on the treated (ATT), which measures the percentage change in energy use that occurs when a heat pump is replaced with a new, more efficient one. We note that equation (1) is a reduced-form equation that cannot disentangle the extent of the rebound effect (if any). Based on existing literature (Greening et al., 2000; Davis, 2008; Sorrell et al., 2009; Linares and Labandeira, 2010; Gillingham et al., 2013), we do not expect any rebound effect to be so strong as to completely erode the technological efficiency gains. We therefore expect λ to be negative.

One concern with equation (1) is that energy consumption and the decision to replace a heat pump might be endogenous. Ideally, equation (1) would thus be estimated using instrumental variable approaches. Unfortunately, we simply do not have valid instruments (see Appendix A). Equation (1), however, includes household-specific fixed effects, which address the potential endogeneity of the decision to replace the heat pump as long as any unobservable house or household characteristics that influence both this decision *and* electricity consumption are approximately constant over time.

In the remainder of the paper, we report results based on the "within" estimator for equation 1, but for good measure also re-ran our models using a first-difference estimation approach, and

comfort and heating fuel bill, but pay less attention to the utilization of a refrigerator. Greening et al's estimate the rebound effect to be 10 and 30% for residential heating. Sorrell et al. (2009) suggest best-guess estimates of the long-run direct rebound effect of 10–30% for residential heating and 1–26% for residential cooling. In Davis (2008), the rebound effect for clothes washers is very small. Linares and Labandeira's argument is based on the low elasticity of residential demand for electricity.

14. We exclude from our sample households whose recently installed heat pumps replaced a heater that uses a different type of fuel (electricity bills would rise for these households, since now electricity is used for heating and cooling, and not just for lighting and appliances). We also exclude the 26 households in our sample with geothermal pumps.

15. All of the household in our study area face the same electricity price, which varied little during the study period. We therefore let **M** capture any effects on demand due to changes in prices. The utility applies a two-part tariff, with a fixed fee plus a constant price per kWh (in other words, they do not apply block pricing).

got virtually identical results. We report t statistics based on standard errors clustered at the household level.

The difference-in-difference approach rests on the assumption that treatment and control units have a common trend (if any). We test whether they do—at least before the "treatment" (replacement of the heat pump)—by estimating a slightly simplified version of equation (1), namely

$$\ln E_{it} = \alpha_i + \beta lnDDays_{it} + \gamma(lnDDays_{it} \times Winter_{it}) + \boldsymbol{m_{it}\delta} + \theta \cdot t + \rho \cdot (t \times TG_i) + e_{it}, \quad (2)$$

where TG denotes that the household is a "changer" and is thus part of the treatment group, $\boldsymbol{m}$ is a vector of month dummies, and $t$ a time trend, using a sample that contains the controls and the "changers" before they change their heat pumps. We test the null that ρ is zero. Failure to reject the null implies that there is no evidence of different trends, at least before the treatment.

### *C. Heterogeneous Effects*

Equations (1) and (2) assume that the proportional effect of changing the heat pump is the same for all households. We check for heterogeneous effects by adding interactions between the treatment dummy and i) dwelling or household characteristics, ii) an incentive-received dummy, and iii) (log) incentive amount. We also construct alternate samples that include only the controls and the incentive recipients, or only the controls and the non-incentive changers.

We do not have any prior expectations on the signs and magnitude of the coefficients on ii) and iii) above. If households attracted into rebate programs are systematically more productive at saving electricity than others (Joskow and Marron, 1992), and we do a good job capturing this heterogeneity with household-specific fixed effects, then there is no particular reason why the treatment effect should be different for them. On the other hand, it is possible that program participants are more productive with the new technology, or better aware of new technologies, or that the efficiency requirements that they must meet to qualify for the incentive are sufficiently stringent to make a difference. And finally, it is possible that incentive itself makes incentive recipients more aware about efficiency and energy usage—and they end up using less energy.

Greening et al. (2000) and Sorrell et al. (2009) discuss the possibility that the effects of efficient technologies may vary with the technology's share of total energy bills, thermal comfort and sensitivity to it, and opportunities to adjust the rate of utilization of the technology. With space heating, for example, "temperature take-back" (adjustment in internal temperature in the home, which is accounted for in part by the physical characteristics of the dwelling and in part by behaviors) for example, may be greater among low-income households, or in developing countries.

These considerations suggest that we should check if the effects of the incentives vary across light and heavy users. We accomplish this with fixed-effects quantile regressions. We adopt Canay's (2011) representation

$$Pr(Y_{it} \leq \boldsymbol{x_{it}\beta}(\tau) + \alpha_i \,|\, \boldsymbol{x_{it}}, \boldsymbol{\alpha_i}) = \tau, \quad (3)$$

where τ denotes a specific quantile, Y is log usage, x is the set of right-hand side variables in equation (1), as well his assumptions, which imply that the fixed effects do not depend on τ and are present in the conditional expectation of $Y_{it}$:

$$Y_{it} = \boldsymbol{x_{it}\beta}(\mu) + \alpha_i + u_{it}, \quad (4)$$

**Table 2: Heating and Cooling Equipment in the Main Survey (N = 1153)**

| Type | (A) N in the main survey (% of main survey respondents) | (B) N changed in last 5 years (% of N in column (A)) | (C) N rebate if changed last 5 years (% of N in column (B)) |
|---|---|---|---|
| Any | 1153 (100.00) | 413 (35.82) | 231 (55.69) |
| Heat pump | 578 (50.13) | 284 (49.13) | 171 (60.21) |
| Geothermal | 26 (2.25) | 18 (69.23) | 18 (100.00) |
| Other | 549 (47.61) | 111 (20.22) | 41 (36.94) |

where $\mu$ denotes the mean.

The simple two-step estimator proposed by Canay transforms the dependent variable into $Y_{it} - \hat{\alpha}_i$, where $\hat{\alpha}_i$ is the estimated fixed effect from "within" estimation, and then applies conventional quantile regression to the transformed dependent variable. Canay shows that this two-step estimator of the slopes is consistent at the usual rate and asymptotically normal when $n$ (here, the number of households) and T (here, the number of billing periods) go to infinity.

## 5. THE DATA

### *A. The Main Survey Sample*

We begin this section with a brief description of the 1153 people that filled out the main survey questionnaire in the fall and winter of 2011. In terms of education and income, 27.32% of the respondents have a college degree and 60% reports that household income is above $120,000 a year. The median home size is 1856 square feet. Based on the utility electricity records, the median electricity usage is about 1400 kWh per billing period (about 16,800 kWh a year, and a monthly bill of about $250). This heavy usage (the statewide average in 2011 was about 12,000 kWh[16]) is in part explained by the large share of homes that rely on heat pumps for heating and cooling.

Table 2 shows that out of 1153 main survey respondents, 413 (35.82%) replaced their heating system over the last five years. Using weights that account for choice-based sampling, the population rate is 30.41%, which corresponds to an annual rate of 6.08%. For comparison, we computed the replacement rate for the South mid-Atlantic region (which includes our survey area) using the micro data from the 2009 Residential Energy Consumption Survey, and found that this too is 6% per year (over 2005–09).

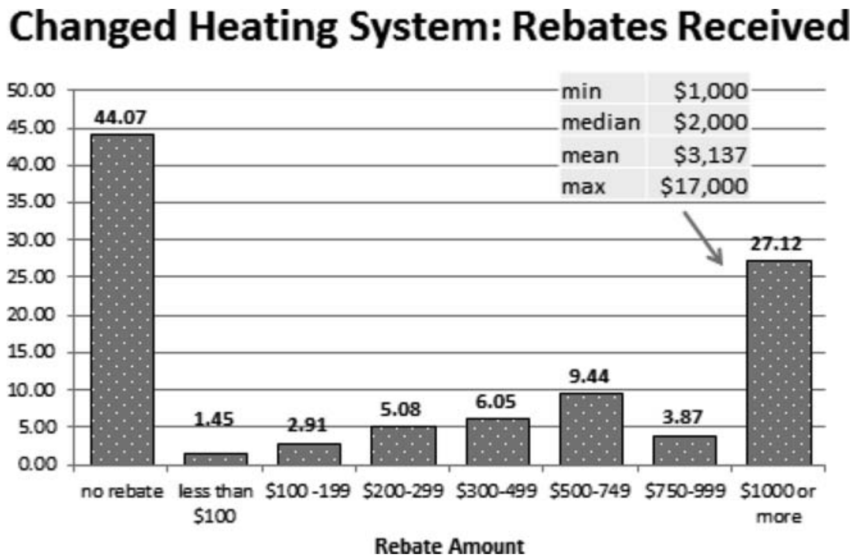
Table 2 also shows that heat pumps are common in our main survey sample: They account for about 50% of the sample,[17] and about half of them were replaced in the last five years.[18] Sixty

16. See http://www.eia.gov/tools/faqs/faq.cfm?id = 97&t = 3 (last accessed 30 July 2013).

17. This figure is based on the respondent-reported information about heating and cooling system at his or her home.

18. MPV indicates that about 60% of the 1940–2000 homes in our study area use heat pumps. For comparison, the US Department of Energy reports that in the southern Mid-Atlantic states heat pumps are used in 20% of the homes, but that figure reflects primarily the urban areas of Maryland, Virginia, the District of Columbia and Delaware, and piped natural gas (the most common heating fuel in the US) is not available in our study region. See the 2009 Residential Energy

**Figure 1: Rebates or Tax Credits Received for Replacing the Heating System. Sample: Fall/Winter 2011 Survey Respondents Who Changed Their Heating System within the Last 5 Years. N = 413.**




percent of these replacements received incentives.[19] Since many incentives were specifically targeted at heat pump and geothermal systems, it is not surprising that the rate at which incentives were received is higher for these two types of heating technologies than for other types (e.g., propane gas and heating oil).

The median cost (before incentives) of a new heating system in the sample from the main survey is $5,000 ($6,000 if a rebate or tax credit was received, $3,500 otherwise, $5,500 for heat pumps, and $26,500 for geothermal systems).[20] Almost 56% of those that replaced any type of heating system availed themselves of a "tax credit or rebate from the federal or state government, the utility or the manufacturer." For almost 40% of this group, the rebate or tax credit was in excess of $500 and, in fact, 27% received a rebate of $1000 or more. We were able to obtain the exact rebate or tax credit amount from 45 respondents whom we re-contacted during the follow-up Phase II phone surveys. For this group, the rebate or tax credit ranged from $1,000 to $17,000; the mean was $3,137 and the median was $2,000 (see Figure 1).

*B. Selection into the Sample*

One overarching concern with the above statistics is that they might be affected by sample-selection bias, so that they do not mirror the true rates in the population of pre-2000, owner-occupied single-family homes and townhomes. We checked for possible sample selection bias using three different approaches.

Consumption Survey, available at http://www.eia.gov/consumption/residential/data/2009/#undefined (last accessed 27 April 2013).

19. By incentive, we mean a tax credit and/or state- or utility-offered rebate.

20. We remind the reader that these were the expenditures on the new systems reported by the respondents in our survey.

**Table 3: Determinants of Participation in the Main Survey: t tests**

| Variable | description | participant = 0 | participant = 1 | t stat | Difference significant at 5%? |
|---|---|---|---|---|---|
| *Dwelling characteristics* | | | | | |
| Log square footage | | 7.4305 | 7.5131 | −7.27 | Yes |
| Year house was built | | 1985.46 | 1984.56 | 1.87 | No |
| Townhome | | 0.1129 | 0.0668 | 5.70 | Yes |
| Brick | | 0.0825 | 0.0971 | −1.59 | No |
| Frame | | 0.1636 | 0.1674 | −0.32 | No |
| average quality | | 0.5798 | 0.6140 | −2.24 | Yes |
| good quality | | 0.0850 | 0.0980 | −1.40 | No |
| fair quality | | 0.2993 | 0.2523 | 3.42 | Yes |
| Basement | | 0.4414 | 0.4844 | −2.59 | Yes |
| Floors | | 1.6543 | 1.6626 | −0.54 | No |
| *Neighborhood (census block group) characteristics* | | | | | |
| Pct White | | 74.2013 | 76.3938 | −5.22 | Yes |
| Pct African American | | 20.6633 | 18.6756 | 5.31 | Yes |
| Pct Asian | | 1.6144 | 1.6002 | 0.40 | No |
| Pct Other Race | | 3.5271 | 3.3183 | 4.45 | Yes |
| Pct Hispanic | | 2.0686 | 1.9817 | 1.98 | Marginal |
| Pct College degree | | 22.4654 | 23.4579 | −4.50 | Yes |
| Pct residents aged 65 and older | | 8.1631 | 8.4623 | −2.79 | Yes |
| Pct residents aged 5 or younger | | 7.1017 | 6.8369 | 5.85 | Yes |
| Pct dwellings built after 1990 | | 32.6704 | 31.2064 | 3.30 | Yes |
| Median Household Income | | 63,276.71 | 65,030.62 | −4.88 | Yes |
| *Electricity usage* | | | | | |
| mean_usage08 | kWh per billing period (month) in 2008 | 1402.28 | 1460.69 | −2.72 | Yes |
| Intensity | Mean_usage08/sqft | 0.9140 | 0.8637 | 3.78 | Yes |
| Intmissing | intensity missing | 0.0575 | 0.0442 | 2.02 | Marginal |
| MPV_heat_heatpump | heat pump | 0.6221 | 0.6214 | 0.42 | No |
| MPV_heat_electric | electric heat | 0.0416 | 0.0450 | −0.54 | No |
| MPV_heat_hotwater | boiler | 0.0282 | 0.0381 | −1.67 | No |
| MPV_heat_hotair | furnace | 0.2974 | 0.2966 | 0.05 | No |

First, we compared dwelling characteristics and Census-based summaries of the local populations across main survey participants (N = 1153) and non-participating households (N = 9956 − 1153 = 8803). The results of the corresponding t tests are displayed in table 3.[21] We found that participants have slightly larger homes and tend to live in neighborhoods with higher incomes and higher shares of White-Caucasian residents, but the differences are modest, even when they are statistically significant (first and second panels of the table). Even more important, participation does *not* depend on the type of heating system (bottom panel of the data). Electricity consumption per billing period is higher among survey participants, but the difference is only 4%.

21. These are unpaired t tests that assume unequal variances.

**Table 4: Determinants of Participation in the Survey: Probit Models of Participation**

| | (i) all delivered letters | | (ii) only households with intensity data (intmissing = 0) | | (iii) all delivered letters | |
|---|---|---|---|---|---|---|
| coeff | t stat | coeff | t stat | coeff | t stat | |
| Constant | −1.06467 | −27.66 | −0.79386 | −11.53 | −1.91258 | −7.23 |
| Intensity | −0.13927 | −3.55 | −0.17272 | −4.32 | −0.0823 | −1.78 |
| Intmissing | −0.26652 | −3.19 | | | −0.20405 | −2.33 |
| round 2 of the survey | | | | | −0.22308 | −2.13 |
| Square footage | | | | | 0.000415 | 4.18 |
| Square footage square | | | | | −5.85E-08 | −2.96 |
| Vintage 1950–60 | | | | | 0.062879 | 0.45 |
| Vintage 1961–70 | | | | | −0.08557 | −0.66 |
| Vintage 1971–80 | | | | | 0.192867 | 1.63 |
| Vintage 1981–90 | | | | | 0.067567 | 0.57 |
| Vintage 1991–2000 | | | | | 0.106941 | 0.71 |
| Townhome | | | | | −0.1336 | −1.99 |
| Brick | | | | | −0.21436 | −1.64 |
| Vinyl siding | | | | | −0.19454 | −1.59 |
| Frame | | | | | −0.19584 | −1.56 |
| Median household income | | | | | 3.61E-06 | 2.27 |
| Pct White | | | | | 0.005915 | 3.72 |
| Pct Hispanic | | | | | 0.019326 | 1.4 |
| Share of homes in the neighborhood with boiler type of heater | | | | | −0.09364 | −0.2 |
| Share of homes in the neighborhood with heat pump | | | | | −0.0321 | −0.35 |
| log L | −3560.92 | | −3379.23 | | −3492.6 | |
| N | 9956 | | 9399 | | 9952 | |

At the same time, electricity intensity (i.e., average usage per billing period divided by the square footage of the home) is slightly lower among participants, due to their larger homes.

Second, we estimated a probit model where the dependent variable is a dummy denoting survey questionnaire completion, and the main independent variable is electricity usage per square foot (table 4, specifications (i)–(ii)). We found that this measure of energy intensity is negatively and significantly associated with the likelihood of participation, but in practice the impact of intensity is very small and has little explanatory power.[22] Augmenting this probit with additional regressors (house characteristics, neighborhood characteristics) does little to improve the fit of the model (table 4, specification (iii)).

Third, we remind the reader that in the follow-up Phase I survey we drew a random sample of 500 households that had received the survey invitation letters back in 2011, but had not filled out the questionnaire. We found phone numbers for 429 and managed to speak to 61 over the phone. The rate at which these households had replaced their heating system since 2007, and received rebates or tax credits, were virtually identical to those reported by the 1153 households in the 2011 survey.[23] Taken together, these findings suggest that if there is selection into the sample, it is probably not very important for the purposes of our analysis.

22. Increasing energy intensity by one standard deviation above the sample mean reduces the probability of participating in the survey by 1.27 percentage points, bringing it from 11.82% to 10.55%. Increasing it by two standard deviations reduces the likelihood of participation by 2.4 percentage points above the sample mean, bringing it to 9.37%.

23. Specifically, 33% of these 61 former non-participants replaced the heating system over the last 5 years, and 55% received an incentive when they did so. The percentages in the 2011 wave were 35.82% and 56%, respectively.

### *C. Sample Construction*

In order to construct the estimation sample we begin with the billing and usage data, and other information, from N = 70 of the households who changed their heat pumps between 2007 and 2011, and from whom we were able to get detailed information about the time of this change and the features of the new heat pump.[24] We supplement this sample using the households with heat pumps from the main survey that had not changed them in the previous five years (N = 394). Because electricity billing has an approximately monthly frequency, and we have usage and billing records from December 2007 to April 2012, the electricity consumption readings form a panel dataset with up to T = 54 observations per household.

We further restrict the final estimation sample to accounts that were active at the time of the main survey in 2011, and, for those that did change their heat pumps, to households that clearly replaced an existing electric heat pump with a new one. We therefore exclude households whose previous heating systems used a different fuel or who fail to report whether there was a fuel switch. We also exclude the 26 households with geothermal systems. This leaves us with monthly electricity usage records over 5 years for N = 53 households who changed heat pumps and N = 282 who did not. All of them had lived on the premises for the entire study period. Further, if a household changed the heat pump in the last five years, and reported the year of the change, but not the exact month, we simply exclude from the usable sample all of the observations from the year of the change.

### *D. Usage and Energy Efficiency Comparisons*

We first check if the controls are similar to the treatment group (those who have changed their heat pump in the last five years) prior to the treatment (replacing the heat pump). Before changing the heat pump, the average usage of electricity per billing period in our treatment group was 1,776 kWh, whereas that in the control group was 1,650 kWh.[25] The log usage means are 7.3635 and 7.2424. Formal t-test results based on log usage and other measures are reported in table 5.[26] These results show that households who changed their heat pump in the last five years tended to use more electricity per billing period before changing the heat pump than the controls. Log intensity (where intensity is usage divided by square feet) is roughly the same in the two groups. Table 6 displays information about house and household characteristics for the treatment and control groups, showing that treatment households are wealthier and "older" than the control households, and live in larger homes. Treatment and control groups, however, live in homes of similar vintages, construction materials, and types.[27]

24. This additional and detailed information was obtained during follow-up Phase II in the summer of 2012. We re-contacted all of the 411 households who had reported changing their heating system in five years prior to the main survey. We managed to interview N = 104 of them. Not all of these 104 households had heat pumps. The reason we re-contacted the household who participated in the main survey is that the main survey questionnaire did not gather sufficiently detailed information about the exact date of replacement of the heating system (heat pump or other) to allow us to see how energy use was affected.

25. These statistics are based on accounts that were active at the time of the main survey and Phase II follow-up in the summer of 2012. The sample is restricted to households with heat pumps and is limited to billing periods with length between 28 and 33 days. We exclude households who changed heat pump between 2007 and 2012, but in doing so replaced heating equipment that used a different fuel.

26. Because observations within a household may be correlated over time, we first computed averages for each household. The t tests reported in tables 5 and 7 use a single figure per household—the household's average over time.

27. Dwelling "vintage" or cohort effects have been found to be important determinants of residential energy use in other studies (Cost and Kahn, 2011). We don't expect such effects to be at play here, given that the control and treatment groups are similar in terms of construction year.

**Table 5: Electricity Usage Comparison between Controls and Treatment Households before the Treatment (Respondents with active accounts, who replace electric heat pumps with electric heat pumps)**

| | control group: mean | treatment group: mean | t statstic of the null of no difference across groups |
|---|---|---|---|
| usage (kWh per billing period [approx. one month] | 1650.36 | 1775.53 | −1.37 |
| log usage | 7.2424 | 7.3635 | −1.95 |
| log usage per day | 3.8338 | 3.8791 | −1.05 |
| log usage per square foot | −0.2777 | −0.3181 | 0.69 |

**Table 6: Dwelling and Household Characteristics: Comparison Across Controls and Treatment Households. (Respondents with active accounts, who have electric heat pumps and/or replace them with electric heat pumps.)**

| | Control group (N = 282): Mean | Treatment group (N = 53): mean | t test statistic of the null of no difference across groups |
|---|---|---|---|
| year house was built | 1989.06 | 1989.34 | 0.2503 |
| size of the house (sq ft) | 1983.81 | 2126.77 | −1.37 |
| townhome dummy | 0.0922 | 0.0377 | 1.7256 |
| brick construction | 0.0638 | 0.0754 | −0.2953 |
| frame house | 0.1206 | 0.1887 | −1.1819 |
| house is of average construction quality | 0.6347 | 0.6792 | −0.6283 |
| house is of good construction quality | 0.0922 | 0.1698 | −1.4149 |
| number of floors | 1.7553 | 1.8301 | −1.3275 |
| household income $120,000 or more (dummy) | 0.3794 | 0.5472 | −2.2409 |
| number of children 0–11 yrs old | 0.468 | 0.2074 | 2.699 |
| number of children 12–18 yrs old | 0.3972 | 0.2264 | 1.964 |
| number of adults 18–65 yrs old | 1.961 | 1.9057 | 0.3551 |
| number of adults 65 yrs old and older | 0.1844 | 0.415 | −2.1642 |
| number of persons in the household | 3.1213 | 2.8077 | 1.8555 |

About 69% of those who changed their heat pump reported receiving an incentive on this purchase. A federal tax credit was present (alone or in conjunction with other incentives) in 62% of these cases. We check whether—prior to the treatment—those households that received a rebate or a tax credit are similar to those that changed their heat pump but did not receive an incentive (table 7). Incentive recipients use somewhat less electricity in total than non-recipients, but the difference is not statistically significant, and consume significantly less on a per square foot basis. Taken together, the results in tables 5 and 7 confirm that it is appropriate for our econometric models to include household-specific fixed effects, and also suggest that there is no particular reason to expect that the treatment effect should be very different across incentive and non-incentive heat pump "replacers."

**Table 7: Electricity Usage Comparison between Households that Changed their Heat Pumps With and Without Incentive, before Changing the Heat Pump. (Respondents with active accounts, who have electric heat pumps and/or replace them with electric heat pumps.)**

| | treatment group (changed heat pump) | | |
|---|---|---|---|
| | No incentive: Mean | Incentive: Mean | T statistic of the null of no difference across groups |
| usage (kWh per billing period [approx. one month]) | 1923.36 | 1716.39 | 1.08 |
| log usage | 7.4428 | 7.3318 | 1.04 |
| log usage per day | 4.0155 | 3.8545 | 1.59 |
| log usage per square foot | −0.1248 | −0.3924 | 3.22 |

**Table 8: Equipment Choices of Incentive Takers and Non-incentive Replacers**

| | no incentive | incentive |
|---|---|---|
| SEER | | |
| average | 14.69 | 15.47 |
| Cost of the new heat pump ($) | | |
| median | 6000 | 6000 |
| average | 6413.41 | 7062.5 |
| max. | 18000 | 18000 |

Incentive recipients and non-recipients also appear to be similar in terms of the energy efficiency of the equipment they bought. In the follow-up Phase II survey we asked respondents to report the cost and describe certain technical aspects of their new heat pumps. For some of those who did not report the SEER of their heat pumps, we were able to recover information from the rebate paperwork filed with the utility. The average SEER of the new heat pump is 14.69 for those who did not receive an incentive, and 15.47 among those who did (see table 8). These figures are very close, indicating only a slightly higher efficiency among incentive takers.[28] As shown in table 8, the median, mean, and maximum costs of the new heat pump are virtually identical across these two groups of respondents.

Those who changed their heat pump without seeking incentives seem to have lower incomes, slightly smaller homes, and larger and younger families than those who did receive incentives, but these differences are not significant at the conventional levels. For example, 26% of the non-incentive households report that their annual household income is greater than $120,000 versus 45% among the incentive recipients (t statistic −1.57). The average homes sizes are 1984 and 2156 sq ft, respectively (t statistic −0.96); the average number of children aged 11 or less 0.45 and 0.12 respectively (t statistic 0.98); the average number of children aged 12–18 is 0.58 and 0.38 (t statistic 0.72), and the average number of adults 65 and older in the household 0.86 versus 1.05 (t statistic −0.58).

28. These figures are not statistically different at the conventional levels (t statistic 0.77).

**Table 9: Determinants of heat pump replacement. Phase II Respondents. N = 60.**

| Reasons for changing the heat pump | All–pct. | Rebate–pct. | No rebate–pct. |
|---|---|---|---|
| Old heating equipment was broken or aging | 85.00 | 89.47 | 77.27 |
| The old heating system one was inadequate | 31.67 | 42.11 | 13.64 |
| I wanted to upgrade to a more energy-efficient system | 16.67 | 21.05 | 9.09 |
| I was doing another renovations at my house | 0.00 | 0.00 | 0.00 |
| I was planning to sell my home | 0.00 | 0.00 | 0.00 |
| I was offered an attractive deal | 1.67 | 2.63 | 0.00 |
| I was offered a rebate or a tax credit | 10.00 | 15.79 | 0.00 |
| I wanted to help reduce emissions | 1.67 | 0.00 | 4.55 |
| My system was the least expensive that still met the requirements for rebate or tax credits | 0.00 | 0.00 | 0.00 |
| I wanted to save money | 0.00 | 0.00 | 0.00 |

**Table 10: Decisions had the Rebate or Tax Credit been Absent Altogether. Phase II Respondents who Received a Rebate. N = 38.**

| What would you have done had there been no rebate? | Pct. |
|---|---|
| would have bought the same | 71.05 |
| would have bought a less expensive system | 15.79 |
| would have bought a system based on a different fuel | 0.00 |
| would have bought another model | 0.00 |
| would have bought a less energy efficient model | 5.26 |
| would have bought a less powerful system | 2.63 |
| I would have done without the system for a while | 7.89 |
| I would have waited before replacing the system | 2.63 |

### *E. Reasons for Replacing a Heat Pump*

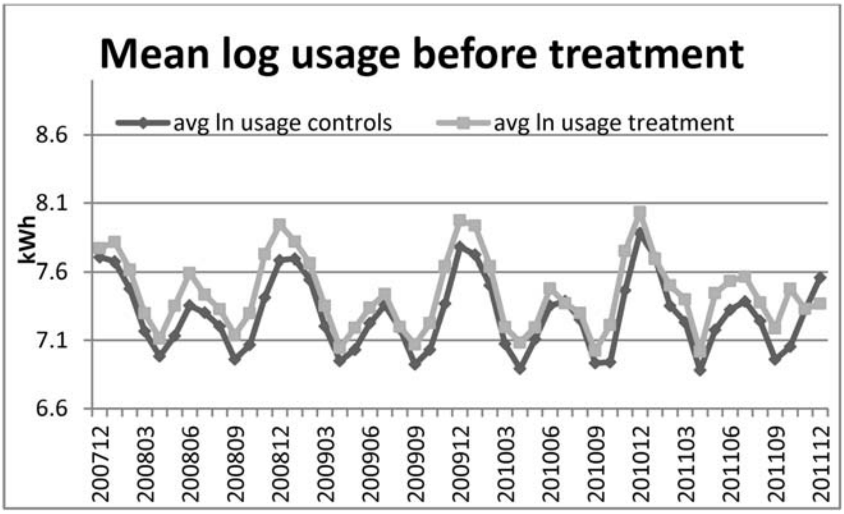
In follow-up Phase II we asked all heat pump “changers” to tell us the reasons why they replaced their heat pumps. Table 9 shows clearly that main reason is that the old heat pump broke or “was aging,” especially among incentive recipients (89% v. 77% among non-recipients).

Only 6 people indicated that “there were offered a rebate or a tax credit,” and 4 of them also selected also selected the response options “the old one broke” or “the old one was aging.” Only 2 of these persons indicated that the rebate or tax credit was the sole reason for replacing the heat pump. Many incentive recipients—about 42%—also said that the “old one was inadequate.” When asked what they would have done in the absence of the rebate or tax credit, most of them (71%) told us they would have bought exactly the same model, 15% said they would have bought a less expensive model, and only about 5% said they would have bought a less efficient system (table 10).

Based on what people told us in the surveys, it appears that free-riding is pervasive in our sample. If we use a restrictive definition of free rider—a household who replaced the heat pump because it was broken or aging, and would have bought exactly the same model in the absence of the incentive--about 50% of our incentive-takers are free riders. If we use a broader definition (they replaced the heat pump because it was broken or aging, but still took the incentive), then 89% of them are free riders.

Those who did not receive incentives generally weren’t sure why they did not apply for the incentives (5 respondents), were not aware of the existence of the incentives (6 respondents),

**Figure 2: Mean Log Electricity Usage for Control Group and Treatment Group before the Treatment (i.e., changing the heat pump).**




claimed (incorrectly) that the incentives were not available at the time they replaced their heat pumps (5 respondents), or simply did not want to deal with the related paperwork or found the rebate too small to bother (total 2 persons).

## 6. RESULTS

### *A. Preliminary Trend Analysis*

Since we use a difference-in-difference approach, we first check that pre-treatment trends are the same for the treatment and control groups. We use two approaches. First, we compute mean log usage by month for control and treatment households before the treatment, which we plot in Figure 2. The graph shows that there are obvious seasonal patterns in electricity consumption for both groups of households. There is no evidence of a trend, and the two groups track each other closely, with the (future) changers generally above the non-changers. This could be because the former's equipment is older and less efficient, or because they have slightly larger homes, or because they are generally heavy users due to preference and household composition (see table 4).

Our second approach is to estimate equation (2) using observations from the controls and the heat pump changers *before* the change. We find no evidence of a trend ($\hat{\theta} = 0.001185$, t statistic 1.24) or of a systematically different trend across changers and non-changers ($\rho = -0.0004913$, with a t statistic of $-0.15$).

### *B. Results from the Difference-in-Difference Approach*

We report the results of regression (1) in table 11.[29] The results show that electricity use is well predicted by weather and time of the year, and that a new heat pump reduces electricity usage by almost 8%. This estimate is in agreement with the engineering estimates used by the utility for purposes of compliance with EmPower Maryland.[30]

29. Full results for these regressions are reported in Appendix B.

30. We obtained a separate set of records from the utility documenting rebate activity in 2011 and 2012. For the 1621 heat pump replacements that received rebates from the utility during that period (and thus comply with the utility's minimum

**Table 11: Main Regression Results. Fixed Effect Models, "within" Estimator. All Standard Errors Clustered at the Household Level. T Statistics in Parentheses. (Respondents with active accounts, who have electric heat pumps and/or replace them with electric heat pumps)**

| Variable | all controls + treatment group |
|---|---|
| Log days in the billing period | 0.5172<br>(12.68) |
| Log degree days | 0.3458<br>(19.39) |
| Log degree days × winter dummy | 0.1416<br>(5.32) |
| Heattreat<br>(new heat pump dummy) | −0.0808<br>(−2.38) |
| Household-specific FE<br>Month × year effects | Yes<br>Yes |
| Nobs | 15063 |

**Table 12: Effect of Changing the Heat Pump: Robustness to Construction of the Sample and Data Cleaning. Fixed Effects Regressions. (Respondents with active accounts, who have electric heat pumps and/or replace them with electric heat pumps.)**

| Sample | Sample used/sample refinement description | Nobs | heattreat (t stat) |
|---|---|---|---|
| (A) | controls who haven't installed any insulations, new windows, etc. in the 5 years before the main survey + treatment group | 10064 | −0.0702<br>(−2.25) |
| (B) | same as in (A); dropped 2 respondents who made additions to the home | 15025 | −0.0824<br>(−2.38) |
| (C) | same as in (B); dropped 1 respondent with photovoltaic system | 15000 | −0.0852<br>(−2.44) |
| (D) | same as in (C); dropped obs with beginning date of billing period in or April 2012 | 14613 | −0.0908<br>(−2.57) |

In table 12 we explore the robustness of this result with respect to various criteria for constructing or further refining the sample. For example, row (A) refers to the same specification as in table 11, but here our control group includes only households who haven't changed their heat pump in the last five years, and haven't installed or replaced insulation, windows, or otherwise improved the thermal integrity of their homes. The average treatment effect is virtually the same as that in table 11.

energy efficiency requirements), the average electricity usage savings imputed by the utility are about 1160 kWh per year. This is a 7.25% reduction if we assume that households use an average of 16,000 kWh a year, and 6.44% if we assume that a household uses on average 18,000 kWh a year. (Households with heat pumps that participated in the main survey use electricity for an average of about 16,000 kWh a year. Those that make up the sample of this paper use an average of about 18,000 kWh a year.)

**Table 13: Effect of Changing Heat Pump. Heterogeneity with Respect to Housing and Household Characteristics. Fixed Effects Regressions. (Respondents with active accounts, who have electric heat pumps and/or replace them with electric heat pumps.)**

| | effect of HEATTREAT on ln E | t stat | Number of treatment households in this situation |
|---|---|---|---|
| All | −0.0808 | −2.38 | 53 |
| home smaller than the median | −0.0578 | −1.02 | 27 |
| home larger than the median | −0.103 | −2.90 | 26 |
| attic insulation absent | −0.0418 | −3.58 | 2 |
| attic insulation present | −0.0823 | −2.34 | 51 |
| home built before 1990 | −0.1663 | −3.13 | 26 |
| household has 2 members or fewer | −0.1038 | −1.92 | 28 |
| household has more than 2 members | −0.0521 | −1.80 | 25 |
| no one in the household older than 65 | 0.0029 | 0.09 | 14 |
| at least one person older than 65 | −0.1113 | −2.16 | 39 |
| sample is controls and treatment households with broken or aging heat | −0.0729 | −2.03 | 44 |

Panels (B)–(D) of table 12 show that the results are robust to, and get statistically stronger with, dropping two households who were found to have done additions to their homes, further excluding a household with a photovoltaic system, and further dropping observations from the last month for which we have usage and billing data, namely April 2012.

We also deployed "long differences," which we construct by taking the difference between the electricity usage of any given billing period and that of the corresponding billing period one year earlier. This approach (not displayed in table 12) estimates the ATT to be a 10% reduction (t statistic −1.59).

In table 13 we look for possible evidence of heterogeneity in the ATT. For simplicity, we have entered one interaction at a time in equation (1). The electricity demand reduction associated with replacing a heat pump ranges from 0 to 15%. The strongest effects are observed for homes built before 1990, larger homes, households with persons aged 65 and older, and homes with attic insulation.

### *C. The Effect of Incentives*

In table 14 we investigate whether the ATT depends on energy efficiency incentives. We begin with creating a sample that is comprised of the electricity usage observations from the controls and the heat pump replacers who did not receive incentives, and fitting equation (1) to this particular sample. The results of this run, displayed in row (A), are striking: The ATT is now much stronger, for an estimated reduction in electricity usage of 16.93% (t statistic −3.02).

In row (B) of table 14 we form a different sample, which includes electricity usage observations from the controls and heat pump "replacers" who did receive incentives. The results are starkly different: The reduction in electricity consumption is virtually nil for those who received an incentive. We get similar results if we restrict the sample to observations from households who

**Table 14: Effect of Changing the Heat Pump: Effect of Incentive. Fixed Effects Regressions. (Respondents with active accounts, who have electric heat pumps and/or replace them with electric heat pumps.)**

| Sample | Households whose electricity usage readings are included in the sample | Nobs | heattreat (t stat) | heattreat × rebate (t stat) | heattreat × lrebate (t stat) |
|---|---|---|---|---|---|
| (A) | controls plus treatment units who did not receive incentives * | 13182 | −0.1855<br>(−3.02) | | |
| (B) | controls plus treatment units who received incentives * | 13923 | −0.0359<br>(−1.01) | | |
| (C) | control and treatment groups ** | 14613 | −0.1832<br>(−2.99) | 0.1476<br>(2.12) | |
| (D) | controls and treatment units who i) did not receive incentives, or ii) received incentives only from the federal government** | 14073 | −0.1853<br>(−3.02) | 0.1051<br>(1.46) | |
| (E) | control and treatment groups; drop if rebate is from manufacturer only** | 14527 | −0.1831<br>(−2.99) | 0.1674<br>(1.97) | |
| (F) | control and treatment groups** | 14613 | −0.1727<br>(−2.85) | | 0.019<br>(1.81) |

*: dropped 2 respondents who made additions to the home and 1 respondent with a PV system.
**: same as *, plus dropped April 2012 usage data.

received a rebate, which means we are comparing their own pre- and post-change usage. This approach produces an estimate of $\lambda$ equal to 0.6% (t statistic 0.15). By contrast, in the no-incentive-only sample the estimated treatment effect is a 14.32% reduction in usage (t statistic −2.90).[31]

In row (C) of table 14 we pool all treatment and control units, and include in the model an interaction between the treatment dummy and receiving an incentive. "Natural" changers reduce usage by 16.74% (t stat. −3.28) while incentive recipients only by 3.5% (t stat −1.02), which confirms the results in rows (A) and (B).[32] When we distinguish for the source of the incentive (rows (D) and (E)) it would seem that recipients of federal tax credits (which are proportional to the cost of the new heat pump) accomplish more substantial electricity usage reductions that the rest of the incentive takers. These results, however, should be interpreted with caution because most incentive takers appeared to combine incentives from different sources, and because the relevant coefficient in row (D) is insignificant at the conventional levels.

We experimented with different ways of entering the actual rebate amount in the model—linearly, as a share of the cost of the new heat pump along with the cost of the heat pump, summarized into broad categories, etc.—and the results generally agree with the notion that the larger the rebate, the less the effect on electricity consumption. For example, row (F) in table 14 includes the treatment dummy and its interaction with the log of rebate amount. The coefficients indicate that electricity consumption decreases by 15.86% among non-rebate takers (t stat−3.11), by 6.22% (t stat −1.97) among those who received a \$300 rebate, by 5.5% when the rebate is \$450 (t stat −1.66) and by insignificant amounts (3% or less) for rebates of \$1,000 or more. Allowing these results to vary with house size or income (by using three-way interactions between *HEATTREAT*,

31. These results are not displayed in table 12 and are available from the authors upon request.
32. These percentages are obtained from the coefficients in table 14 by applying the transformation exp(estimated coefficient)−1. Standard errors and t statistics for these percentages are derived using the delta method.

**Table 15: Average Treatment Effect of Incentive: Free Riders and Motivation for Changing the Heat Pump. Fixed Effects Regressions. (Respondents with active accounts, who have electric heat pumps and/or replace them with electric heat pumps.)**

| | N | heattreat | t stat | lrebatetreat | t stat |
|---|---|---|---|---|---|
| *Specification with HEATTREAT dummy* | | | | | |
| drop strict free riders | 14233 | −0.1255 | −2.79 | | |
| drop old heat pump was broken | 13923 | −0.1000 | −2.50 | | |
| drop old heat pump was aging | 14048 | −0.0806 | −1.39 | | |
| drop old heat pump inadequate | 14332 | −0.0976 | −2.17 | | |
| drop old heat pump was broken or aging | 13127 | −0.1338 | −1.43 | | |
| *Specification with HEATTREAT dummy and log incentive amount* | | | | | |
| base model | 15063 | −0.1666 | −2.76 | 0.0192 | 1.85 |
| drop strict free riders | 14233 | −0.1709 | −2.79 | 0.0147 | 1.19 |
| drop old heat pump was broken | 13923 | −0.2241 | −3.05 | 0.0231 | 1.86 |
| drop old heat pump was aging | 14048 | −0.1414 | −1.77 | 0.0162 | 0.93 |
| drop old heat pump inadequate | 14332 | −0.1694 | −2.31 | 0.0213 | 1.9 |
| drop old heat pump was broken or aging | 13127 | −0.1090 | −2.52 | −0.0064 | 0.0027 |

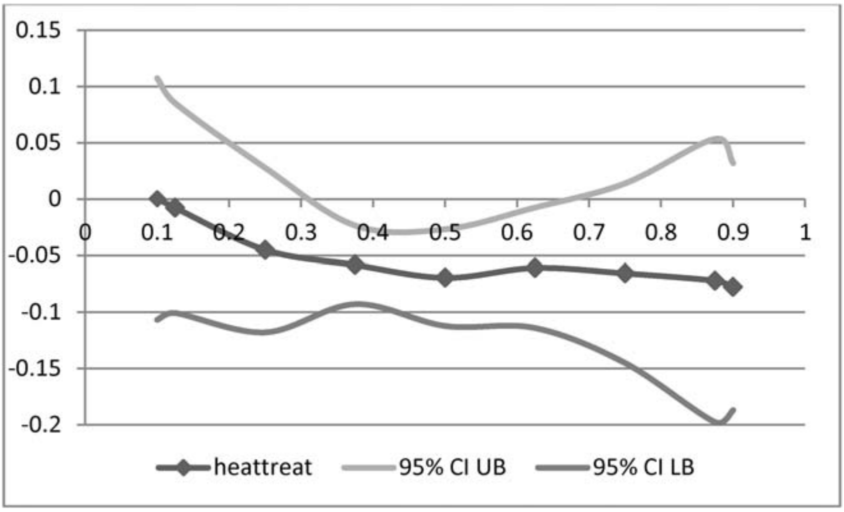
the rebate dummy or log rebate, and a high income/large house dummy, or by restricting the high/low income or large/small house households) does not affect the results, nor does normalizing usage by house size.[33]

The fact that usage actually (weakly) increases with the size of the incentive points to two possibilities: That the incentives reduce the cost of the energy services for recipients, which now demand more energy services, and hence more electricity, or that this effect is due to persons who are upsizing their systems, and thus experience a post-change increase in usage. We explore these possible explanations in table 15, where we report the results of regressions where we exclude from the sample persons who replaced a broken or aging system (and would have purchased the same model even in the absence of the incentive), persons who replaced a broken and/or aging system, and persons who stated they changed the old heat pump because it was "inadequate."

The ATT of changing the heat pump is stronger when we exclude observations from these persons. Dropping these groups from the usable sample, however, does little to the estimated slope of log incentive, which is similar to the base model in table 12.

33. We also examined a possible technical explanation. Electric heat pumps do not perform particularly well at cold temperatures (below 37° F), and so many households in our study region have a propane gas "back-up" which can be deployed on very cold days. If for some reason the households who received incentives purchased units that perform better at low temperatures and reduce reliance on back-up fuel on particularly cold days, then they might still have reduced overall energy use, even though their electricity consumption has not decreased. We checked the description of the heat pump technology reported by our interviewees, and gas back-ups are just as common among incentive and non-incentive households. We also tested the abovementioned conjecture by adding a two-way interaction between the treatment dummy and the winter season, plus a three-way interaction between the treatment dummy, incentive or log incentive amount, and a winter dummy. The regression results indicate that the effect of changing the heat pump is uniform across seasons for both incentive and non-incentive households. We conclude that technical differences in the equipment are unlikely to be driving our results.

**Figure 3: Average Treatment Effect on the Treated from Fixed Effects Quantile Regression.**




*D. Fixed-Effects Quantile Regressions*

In Figure 3 we plot the coefficients on the treatment dummy, *HEATTREAT*, for selected quantiles $\tau$ from fixed effects quantile regressions with the same right-hand side variables as equation (1). The quantile regression results indicate that, conditional on the covariates, the effect of changing the heat pump is smallest and statistically insignificant at the lowest quantiles—namely the 10th and 12.5th (0.000236, t statistic 0.004, and $-0.0079$, t statistic $-0.17$).[34] By about the 40th percentile, the coefficient is $-0.0582$ (t statistic $-3.296$). The coefficient is very stable (about $-0.07$ to $-0.08$) for percentiles greater than the 50th, although it is not statistically significant at the top quantiles.

When we enter the interaction of *HEATTREAT* with the incentive dummy, the fixed effects quantile regressions (summarized in Figure 4) suggest that households who did not receive incentives reduced electricity usage by 10% or more, even at the lowest quantiles. The largest reductions are observed at the 50th percentile (about 14% reduction). At the high percentiles the electricity demand reduction are similar to those at the low percentile. The story is completely different for households that received incentives: Except for the highest percentiles, these households appear to have increased usage. At the low usage percentiles, electricity usage actually increases by almost 16%.

Figure 5 displays the effect of treatment on log electricity demand for selected incentive values. At zero incentive, the effects at different percentiles are similar to those for non-incentive changers shown in Figure 4. At \$450, households in the 10th percentile increase usage by about 11%. The effect becomes smaller as we increase $\tau$, and by the 90th percentile usage decreases by about 6%. The pattern is similar for a \$1,000 incentive, where the bottom 10% and the top 10% of the distribution of usage, experience a 14% increase and 5% increase, respectively. The effect is positive but small at the other quantiles.

34. The t statistics are based on bootstrapped standard errors.

**Figure 4: Average Treatment Effect on the Treated from Fixed Effects Quantile Regression. Model with Interaction between Heat Pump Treatment Dummy and Incentive Dummy.**

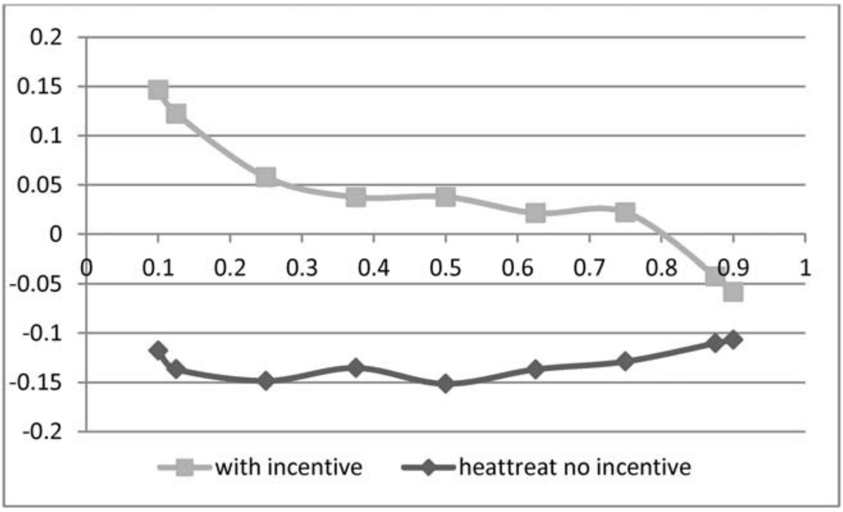
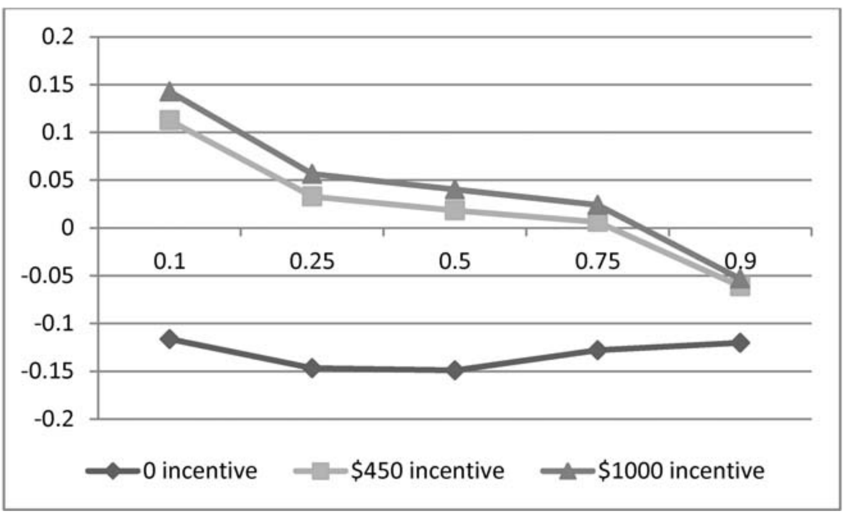



**Figure 5: Average Treatment Effect on the Treated from Fixed Effect Quantile Regression. Model with Heat Pump Treatment Dummy and Log Incentive.**




## 7. CONCLUSIONS

We have developed a unique dataset based on an original survey of households, combined with data on home characteristics and neighborhood location, as well as monthly electricity usage records, utility program participation, and other sources, and used it to investigate three key questions about energy-efficiency upgrades and the role of energy-efficiency incentives. We have focused on heat pumps and used a difference-in-difference estimation approach where the dependent variable is log energy usage in a billing period. We account for unobservables (and thus the possible endogeneity of the decision to change the heat pump and/or apply for an incentive on the purchase) using household-specific fixed effects.

Overall, we have found that replacing an existing heat pump with a new one does indeed reduce electricity usage. The average treatment effect on the treated is an 8% reduction, the effect being more pronounced for households with larger homes, for homes with insulation, and for households with elderly persons.

From a policy perspective the more important question is whether households who have received energy-efficiency incentives reduce usage to a different extent than households who do not avail themselves of such incentives. Free riding is pervasive in our sample (50–89% of incentive recipients), but we have no a priori reason to believe that free riders are any less likely to reduce energy usage. Moreover, incentive takers and non-takers are similar in terms of the manufacturer-specified energy efficiency rating and expenditure on their new heat pumps.

What we find here is striking: The average treatment effect is a 16% electricity usage reduction among non-recipients, and virtually nil among incentive recipients. Further controlling for the rebate amount suggests that the larger the rebate, the smaller (in absolute value) the reduction in electricity usage. At $1000 and more, there are virtually no reductions in usage. This happens despite the fact that incentive takers and the other households who changed their heat pumps are similar in terms of the efficiency and the cost of the new equipment they purchase.

These findings have important implications in terms of the cost-effectiveness of the $CO_2$ emissions reductions attained through reductions in electricity usage. Assuming an equipment lifetime of 10 years, and 0.608 kg $CO_2$ emissions avoided per kWh saved,[35] if incentive recipients reduced usage to the same extent as non-incentive households (by 15.86%), then a $450 rebate would attain $CO_2$ emissions reductions at the cost of $23.56 per metric ton. This compares very favorably with social cost of carbon figures—about $21—typically used by the US Environmental Protection Agency in its analyses (Greenstone et al., 2013). The cost-effectiveness of a $450 rebate remains good ($31.51/ton $CO_2$) when we use the average $CO_2$ emissions rates for the eGRID sub-region that includes Maryland (1001.72 lbs/MWh), and when, as recommended in the eGRID documentation (Abt Associates, 2014), we use the non-baseload emissions rates ($20.20/ton $CO_2$).[36]

If we assume that the effect of replacing a heat pump is an 8% reduction in usage for incentive takers and non-takers alike, then the cost per ton of $CO_2$ saved with a $450 rebate is $46.24 if we use the utility-recommended emissions rate, $61.84 if we use the eGRID average emissions rate, and $39.65 if we use the eGRID non-baseload emissions rate.

But when we recognize that incentive takers reduce electricity usage to a lesser extent, and larger incentives are accompanied by smaller and smaller usage reductions, we find that only for very low incentive amounts would the cost effectiveness of $CO_2$ emissions reductions from incentive takers be reasonable. For a $450 incentive, for example, each ton of $CO_2$ reduced costs $68.05 if we use the utility-recommended emissions rate, and $58.35 if we use the eGRID non-baseload emissions rate. The cost increases quickly as the incentive is raised. At the mean incentive for the sample of this paper, $2000, the cost per ton of $CO_2$ ranges from $514 to $802, depending on the emissions rate used.

35. This emissions rate is the metrics equivalent of that used by the utility in its calculations for the state energy agency. For comparison, the eGRID system developed by the US Environmental Protection Agency (Abt Associates, 2014) estimates the average annual emissions rate in the PJM Interconnection to be 1001.72 lbs/MWh, or 0.455 kg per kWh..

36. The non-baseload emissions rates for the sub-region is 1562.72 lbs/MWh.

Our results—extreme rebound effects among incentive takers—suggest that households do take into account capital costs when computing the total cost of the energy services from the equipment they are purchasing, a point that was unclear in previous literature (see Turner, 2013, for a discussion). In our study, the reduction in capital expenditures made possible by the incentives must have lowered the cost per unit of energy services to a point sufficient to trigger a large increase in the demand for these energy services. Studies in other settings (e.g., Boomhower and Davis, 2013) have found similar evidence for cooling equipment (air conditioners) but not for refrigerators, suggesting that thermal comfort may be especially sensitive to it.[37]

We also find that many of our incentive takers may have used the incentive to upsize their system—a possibility recognized in Greening et al. (2000) and Van Den Bergh (2011)—since the old one was "inadequate." Quantile regressions show that rebate takers at lowest end of the distribution of electricity usage, conditionally on the covariates, actually *increase* usage after they replace their heat pumps. This is an additional unintended consequence of offering energy-efficiency incentives: With certain types of equipment, and for a non-negligible share of the universe targeted by the rebates, the rebate or tax credit may be utilized to upgrade the system size or increase utilization, with little or no impact on overall usage or emissions.

It might be possible to avoid unintended consequences (free-riding and upsizing) by appropriately targeting the incentives. For example, engineering calculations[38] suggest that considerable savings in electricity usage can be realized by replacing equipment that is "middle aged" but not yet at the end of life. If owners of these systems are not planning to replace any time soon, they are unlikely to "free ride" replacement incentives. It remains an open question—which hopefully will be explored in future research—whether such incentives would deliver cost-effective $CO_2$ emissions reductions, given the possible implementation difficulties and the fact that the uptake is not known a priori.

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37. This does not necessarily mean that the non-incentive households did not experience rebound effects. These households' rebound effects, if they were present, were sufficiently small to results in net electricity usage reductions.

38. See http://www.energydepot.com/pgect/ (last accessed 28 February 2014).

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## APPENDIX A: DETERMINANTS OF HEAT PUMP REPLACEMENT AND SEEKING INCENTIVES

To look for possible determinants of the decision to replace a heat pump, we ran probit models based on the sample of households from the main survey who have heat pumps (N = 578). The dependent variable of these probit models is whether this heat pump was changed in the previous 5 years.

The results for three alternative specifications are displayed in table A.1. They show that housing and household characteristics have very modest explanatory power. They are unsuitable as possible instruments for the decision to replace a heat pump for three reasons. First, their explanatory power is modest. Second, they fail the exclusion restriction: They likely affect energy consumption directly as well as via the decision to replace a heat pump. Third, they are constant over the study period of our panel dataset with the monthly meter readings, and so they get absorbed into the household fixed effects in equation (1).

Likewise, electricity prices proved unsuitable as instruments, because they do not vary across households and vary only very little over time, whether by themselves or interacted with household characteristics. It is even more difficult to find instruments for the decision to seek an incentive:

Table A.2 displays the results of probit models evaluating the impact of observables on the likelihood of receiving a rebate. The sample is restricted to the households from the main survey who replaced their heat pumps during the previous 5 years (n = 284), and the dependent variable is whether they received an incentive for it. Most dwelling and household characteristics have little or no explanatory power.

**Table A.1: Determinants of changing the heat pump: Probit model. Dep. Var.: changed heat pump in the last 5 years. Sample: Fall/Winter 2011 main survey respondents who have heat pumps (N = 578).**

| | dwelling characteristics | | dwelling and household characteristics | | dwelling and household characteristics, plus expectations that electricity price will increase | |
|---|---|---|---|---|---|---|
| | coeff | t stat | coeff | t stat | coeff | t stat |
| Constant | −0.8745 | −1.84 | −0.84001 | −1.61 | −0.89825 | −1.72 |
| Square footage | 0.000866 | 2.18 | 0.000922 | 2.12 | 0.000817 | 1.86 |
| Square footage squared | −2.05E-07 | −2.37 | −2.27E-07 | −2.39 | −2.06E-07 | −2.16 |
| Floors | −0.17328 | −1.25 | −0.09709 | −0.67 | −0.08769 | −0.6 |
| Townhome | −0.25297 | −1.14 | −0.39071 | −1.62 | −0.38108 | −1.58 |
| Average | 0.186727 | 1.32 | 0.233508 | 1.56 | 0.259376 | 1.73 |
| Good | 0.484581 | 2.12 | 0.544213 | 2.32 | 0.560542 | 2.38 |
| Brick | −0.04712 | −0.2 | −0.20433 | −0.8 | −0.1891 | −0.74 |
| Frame | 0.131609 | 0.83 | 0.137128 | 0.82 | 0.130651 | 0.78 |
| House age | 0.007871 | 1.52 | 0.008296 | 1.53 | 0.008552 | 1.58 |
| Income > $120000/year | | | 0.226035 | 1.87 | 0.212954 | 1.75 |
| Some college | | | 0.020685 | 0.14 | 0.010688 | 0.07 |
| College degree | | | −0.13208 | −1.05 | −0.10536 | −0.83 |
| Number of persons in the household | | | −0.09943 | −2.42 | −0.09978 | −2.43 |
| "price of electricity will increase" opinion dummy | | | | | 0.245796 | 2.2 |
| Nobs | 578 | | 548 | | 548 | |
| log L | 18.83 | | 32.26 | | 37.12 | |
| p value | 0.0267 | | 0.0022 | | 0.0007 | |

**Table A.2: Determinants of receiving rebates or tax credits: Probit model. Dep. Var.: rebate. Fall/Winter 2011 main survey respondents who have heat pumps and have changed them within the last 5 years (N = 284).**

| | dwelling characteristics | | dwelling and household characteristics | | dwelling and household characteristics, plus expectations that electricity price will increase | |
|---|---|---|---|---|---|---|
| | coeff | t stat | coeff | t stat | coeff | t stat |
| Constant | −0.158732 | −0.21 | 0.6270392 | 0.73 | 0.5785101 | 0.66 |
| Square footage | 0.0009473 | 1.47 | 0.0005416 | 0.74 | 0.00053 | 0.72 |
| Square footage square | −1.98E-07 | −1.4 | −9.78E-08 | −0.59 | −9.64E-08 | −0.59 |
| Floors | −0.127566 | −0.63 | −0.092508 | −0.43 | −0.082707 | −0.38 |
| Townhome | 0.117019 | 0.32 | 0.2168147 | 0.52 | 0.2213513 | 0.52 |
| Average | −0.01355 | −0.06 | −0.058716 | −0.25 | −0.054309 | −0.23 |
| Good | 0.1717329 | 0.51 | 0.1482948 | 0.42 | 0.1557663 | 0.44 |
| Brick | 0.1679723 | 0.48 | 0.0943495 | 0.24 | 0.1057603 | 0.27 |
| House age | −0.016781 | −2.11 | −0.017904 | −2.11 | −0.017707 | −2.08 |
| Income > $120,000/year | | | 0.2558928 | 1.44 | 0.2521966 | 1.42 |
| Some college | | | 0.0895256 | 0.41 | 0.0846584 | 0.38 |
| College degree | | | 0.0188861 | 0.1 | 0.0222983 | 0.12 |
| Number of persons in the household | | | −0.188763 | −2.82 | −0.18823 | −2.81 |
| "price of electricity will increase" opinion dummy | | | | | 0.0668518 | 0.4 |
| Nobs | 284 | | 264 | | 264 | |
| LR stat. of the null that all slopes are zero | 11.86 | | 17.91 | | 18.08 | |
| p value | 0.1677 | | 0.1184 | | 0.1547 | |

**Appendix B: Main regressions results. Fixed effects model, "within" estimator. All standard error clustered at the household level. T statistics in parentheses. Respondents with active accounts, who have electric heat pump and/or replace them with electric heat pumps. N = 15,063.**

| variable | coefficient | t stat. |
|---|---|---|
| intercept | 2.6512 | 15.97 |
| lbillingdays | 0.5172 | 12.68 |
| ldegreedays | 0.3458 | 19.39 |
| ldegreedayswinter | 0.1416 | 5.32 |
| heattreat | −0.0808 | −2.38 |

| monthyear effects | coefficient | t stat | monthyear effects cont'd | coefficient | t stat. |
|---|---|---|---|---|---|
| 200801 | −0.0108 | −1.29 | 201003 | −0.2077 | −8.58 |
| 200802 | −0.1062 | −7.72 | 201004 | −0.1332 | −4.79 |
| 200803 | −0.1651 | −10.21 | 201005 | 0.8238 | 5.17 |
| 200804 | −0.0326 | −1.19 | 201006 | 0.8622 | 5.23 |
| 200805 | 0.8444 | 5.36 | 201007 | 0.8583 | 5.23 |
| 200806 | 0.8723 | 5.44 | 201008 | 0.8237 | 5.09 |
| 200807 | 0.8533 | 5.4 | 201009 | 0.7200 | 4.56 |
| 200808 | 0.8483 | 5.41 | 201010 | 0.6552 | 3.99 |
| 200809 | 0.7936 | 5.07 | 201011 | −0.0552 | −2.92 |
| 200810 | 0.6961 | 4.18 | 201012 | 0.0316 | 1.07 |
| 200811 | −0.0849 | −4.78 | 201101 | 0.0076 | 0.42 |
| 200812 | 0.0052 | 0.38 | 201102 | −0.1275 | −7.57 |
| 200901 | 0.0107 | 0.7 | 201103 | −0.1729 | −8.68 |
| 200902 | −0.0781 | −5.33 | 201104 | −0.0239 | −0.8 |
| 200903 | −0.1962 | −11.12 | 201105 | 0.8302 | 5.1 |
| 200904 | −0.1068 | −4.29 | 201106 | 0.8380 | 5.08 |
| 200905 | 0.8261 | 5.26 | 201107 | 0.8611 | 5.2 |
| 200906 | 0.8127 | 5.11 | 201108 | 0.7938 | 4.91 |
| 200907 | 0.8547 | 5.3 | 201109 | 0.7476 | 4.71 |
| 200908 | 0.8096 | 5.21 | 201110 | 0.7001 | 4.21 |
| 200909 | 0.7616 | 4.86 | 201111 | −0.0775 | −3.87 |
| 200910 | 0.6624 | 4.04 | 201112 | −0.0354 | −1.73 |
| 200911 | −0.0623 | −2.96 | 201201 | −0.0558 | −3.1 |
| 200912 | 0.0148 | 0.79 | 201202 | −0.1450 | −7.47 |
| 201001 | −0.0003 | −0.02 | 201203 | −0.1903 | −6.34 |
| 201002 | −0.1078 | −5.26 | | | |