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# Leveraging the Smart Grid: The Effect of Real-Time Information on Consumer Decisions

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# LEVERAGING THE SMART GRID: THE EFFECT OF REAL-TIME INFORMATION ON CONSUMER DECISIONS - ENVIRONMENT WORKING PAPER No. 127

**by Dr. Nicholas Rivers, University of Ottawa / OECD**

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# LEVERAGING THE SMART GRID: THE EFFECT OF REAL-TIME INFORMATION ON CONSUMER DECISIONS

## ABSTRACT

Smart meters have the potential to have a significant effect on the electricity market through two mechanisms. First, they make it possible for electricity consumers to obtain information in real-time about the quantity of electricity consumed as well as the price of electricity. This information improves the consumer's ability to optimise electricity consumption decisions, and likely makes electricity consumption more salient to consumers. Second, smart meters make it possible for consumers to be exposed to electricity prices that vary over time, to better reflect scarcity in the electricity market.

This report reviews the literature on the impact of real-time information provision on consumer decision-making. In addition, it describes the results of a study in which about 7000 households in Ontario, Canada were provided with in-home displays linked to smart meters that provided real-time feedback on electricity consumption. The results show that electricity consumption declines by about 3% as a result of information feedback, that the reduction in demand is sustained for at least five months, and that it is highly correlated with outdoor temperature. However, although households reduce electricity consumption on average when exposed to real-time feedback, the findings suggest that real-time information has an ambiguous effect on household responsiveness to electricity price changes.

*Keywords*: Electricity demand, energy conservation, information provision, time-of-use pricing.

*JEL codes*: D12, L94, Q41, Q48

# TIRER AVANTAGE DES COMPTEURS INTELLIGENTS : L'EFFET DE L'INFORMATION EN TEMPS REEL SUR LES DECISIONS DU CONSOMMATEURS

## RÉSUMÉ

Les compteurs intelligents peuvent avoir un effet significatif sur le marché de l'électricité grâce à deux mécanismes. Premièrement, ils permettent aux consommateurs d'électricité d'obtenir des informations en temps réel sur la quantité d'électricité consommée ainsi que sur le prix de l'électricité. Cette information améliore la capacité du consommateur à optimiser les décisions de consommation d'électricité, et rend probablement la consommation d'électricité plus importante pour les consommateurs. Deuxièmement, les compteurs intelligents permettent aux consommateurs d'être exposés à des prix de l'électricité qui varient au fil du temps, afin de mieux refléter la pénurie sur le marché de l'électricité.

Ce rapport examine la littérature sur l'impact de l'information en temps réel sur la prise de décision des consommateurs. En outre, il décrit les résultats d'une étude dans laquelle environ 7000 ménages ontariens ont reçu des écrans relies à des compteurs intelligents qui ont fourni une rétroaction en temps réel sur la consommation d'électricité. Les résultats montrent que la consommation d'électricité diminue d'environ 3% par suite de la rétroaction, que la réduction de la demande est maintenue pendant au moins cinq mois et qu'elle est fortement corrélée avec la température extérieure. Les résultats suggèrent que l'information en temps réel a un effet ambigu sur la réaction des ménages aux variations des prix de l'électricité.

*Mots clés*: Demande d'électricité, conservation d'énergie, provision de l'information, tarification en fonction de l'heure de consommation.

*JEL codes*: D12, L94, Q41, Q48

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## EXECUTIVE SUMMARY

Electricity is a unique commodity for a number of reasons, but of particular importance is that it is difficult to store. As a result, supply and demand for electricity must be matched on a real-time basis. This requirement has long been at odds with the signals that households receive. In particular, households typically face flat electricity tariffs, which do not provide incentives to conserve power at times when such behaviour would be most useful. In addition, households typically cannot observe the wholesale market price or the amount of electricity that they consume in real-time, so that they do not have the basis to make well-informed decisions about their electricity consumption.

New technologies are quickly changing both of these long-standing features of the electricity market. Digital ("smart") electricity meters are replacing analogue meters in many regions of the world. Unlike analogue meters, digital meters record electricity consumption at a fine-grained interval, potentially enabling households to be exposed to prices that vary over time of day. Additionally, when paired with a dedicated feedback technology, smart meters can communicate electricity prices and electricity consumption in real time to households, which provides them with a better informational basis on which to make electricity consumption decisions. This report focuses on a particular type of real-time feedback technology, in-home displays (IHDs), which provide consumers with real-time information about electricity consumption, price and expenditures.

Such high-quality information should increase the ability of the consumer to optimise decisions relating to electricity consumption. However, it is unclear how consumers will respond to the installation of IHDs. In particular, optimising consumers may respond by either increasing or decreasing electricity demand, depending on the nature of their perceptions of electricity consumption and price before the installation of the IHDs. Likewise, IHDs may make consumers more or less responsive to changes in electricity price, depending on how consumers' pre-IHD beliefs reflected actual electricity prices. Moreover, the installation of an IHD may also increase the attention that consumers devote to their electricity consumption, and cause changes in consumption as a result. Understanding how consumers respond to more information therefore rests more on empirical than on theoretical results.

The empirical literature on the impact of real-time feedback via IHDs on electricity demand has produced mixed results. Early pilot programmes developed by electric utilities typically suggest that providing households with real-time feedback on electricity demand causes a substantial reduction in electricity consumption. However, these early studies often do not use methods that would be considered appropriate today, or they do not report enough information on methods, leading to doubts about their findings. More recent studies use high-resolution (e.g. hourly) data to compare electricity consumption from households with and without in-home displays, using either quasi-experimental or experimental research designs. These studies suggest that IHDs can induce meaningful reductions in electricity consumption in contexts where the price for electricity is high. However, there are few such high-quality studies, and most of those that have been conducted focus on particular contexts such that results may not necessarily generalise to a wider population.

This report also provides a review of a recent study that sheds new light on the effect of real-time IHD feedback on consumer electricity demand. The study evaluates a programme that resulted in approximately 7000 households in Ontario, Canada, being provided with an in-home electricity display. It uses a quasi-

experimental approach to assess the impacts of real-time IHD feedback on household electricity demand, by leveraging the fact that IHDs are rolled out to households over a one-year period. This context enables a longitudinal approach to estimating the impact of IHD feedback, in which household electricity consumption with an IHD is compared to consumption in the same household before receipt of an IHD, controlling for trends experienced by other households whose IHD status does not change.

Based on this approach, several important findings are reported. First, the receipt of an IHD results in a reduction in electricity demand of around 3% overall. This result suggests that either (a) households underestimated their expenditures on electricity prior to receiving an IHD, and the additional information caused them to reduce consumption, and/or (b) the receipt of the IHD caused electricity consumption to become more 'visible' to households, and led them to conserve electricity independently of the response to improvements in the quality of information. The results also suggest that household electricity conservation in response to real-time feedback provided via IHDs is concentrated in the autumn and winter heating seasons. The response by households is roughly uniform throughout the day, and does not appear to be caused bythe time-of-use pricing schedule.

The study found that household electricity conservation in response to IHD feedback persists for at least five months following the receipt of the display. Although it is not possible to confidently identify the mechanisms by which households respond to the IHD with the data available in this study, this finding suggests that households respond to real-time feedback in part by adjusting thermostat settings downwards or investing in durable energy efficiency improvements that result in lower space heating demand.

# 1. INTRODUCTION[1]

The market for electricity is evolving rapidly. Electricity generation is no longer uniquely the domain of large vertically integrated electricity firms, as it was for most of the last century. Instead, electricity is increasingly generated in a less centralised manner, by independent generators, sometimes in deregulated electricity markets. Electricity generation technologies are also rapidly changing, with renewable electricity sources becoming increasingly cost-competitive with fossil fuel generation. Consumers are obtaining the technologies required to generate electricity themselves in a decentralised manner, such as with rooftop solar, or the technologies to manage their electricity demand with much more flexibility than previously available, such as with home electricity storage and "smart" thermostats. These changes have important implications for electricity generation companies, electricity consumers, and the environment.

This report focuses on a particular set of technologies that is part of the rapid changes taking place in the electricity market—the "smart" meter and associated feedback technologies in the residential sector. Smart meters record electricity consumption and also act as communication devices, relaying information on electricity consumption to the distribution utility, and also potentially providing similar information to the household. Smart meters can be paired with real-time feedback technologies to improve the communication of information about electricity consumption and price to the household.

Paired with in-home feedback technologies, smart meters can have an important impact on the electricity market because of two specific features.[2] First, smart meters enable the communication of *real-time* information to consumers about both electricity consumption and price. In contrast, with a standard (analogue) electricity meter, consumers only find out their consumption of electricity when electricity bills arrive, i.e. usually at monthly or bi-monthly intervals. For this reason, smart meters improve information availability to residential households, and enable improved electricity consumption decision-making by households. Closely related to this point, smart meters and feedback technologies may make electricity consumption more salient to households and, thus, can directly encourage conservation. Second, smart meters enable time-varying electricity pricing. Economists have long advocated for time-varying wholesale prices to be passed on to consumers, arguing that the flat tariffs normally used in the residential sector suppress potentially cost-effective demand response (Borenstein et al., 2002). Because they are digital devices, smart meters can facilitate the implementation of virtually any type of tariff structure, including those that vary over time. In contrast, with a standard (analogue) electricity meter, implementing time-varying rates is difficult or impossible.

These two features of smart meters may have important impacts for electricity markets and the environment. In particular, by making consumers aware of their electricity consumption, smart meters and feedback technologies improve the ability of households to optimise their electricity consumption, potentially reducing electricity demand. Further, they may help make electricity consumption more salient to residential consumers, and promote electricity conservation directly as a result. These are *behavioural* avenues through which smart meters and feedback technologies can reduce electricity demand. In addition,

[1] Some of the research presented here was conducted by Steve Martin and the author of this report and is also reported in the paper by Martin and Rivers (2015).

[2] This report focuses only on the direct impacts of smart meters on household electricity consumption. Smart meters also confer other benefits, such as improved ability by the electricity distribution company to detect electricity theft, improved ability to manage electricity flows on the electricity network, and reduced costs for electricity meter reading. These benefits do not accrue to the household directly, and are not the focus of this report.

smart meters enable consumers to conserve electricity when supply is constrained by facilitating dynamic electricity pricing. This is a *market-based* avenue through which smart meters can influence electricity demand. All of these mechanisms could have important environmental implications.

Rollout of smart meters to residential customers is underway in many countries of the world, as shown in Table 1. In Canada and the United States, approximately half of all residential meters have been replaced by smart meters as of 2016. In the United Kingdom and France, the rollout of smart meters to households lags behind the rollout in North America. In Ontario, the focus of part of this report, the rollout of smart meters to residential customers was completed by 2010, making it an interesting case study for understanding the potential impacts of smart meters and associated feedback technologies on consumer electricity demand.

**Table 1. Residential smart meter rollout in selected countries and regions**

| Region | No. residential smart meters | No. residential accounts | Smart meter penetration | Year |
|---|---|---|---|---|
| France | ≈1,500,000 | ≈29,000,000 | ≈5% | 2016 |
| Germany | ≈1,600,000 | ≈40,000,000 | ≈4% | 2014 |
| Italy | ≈26,000,000 | ≈26,000,000 | 100% | 2015 |
| Ontario, Canada | ≈5,000,000 | ≈5,000,000 | 100% | 2016 |
| United Kingdom | ≈3,500,000 | ≈27,000,000 | ≈13% | 2016 |
| United States | 57,107,785 | 131,864,192 | ≈43% | 2015 |

*Sources*: *France*: metering.com, https://www.metering.com/reports/linky-smart-meter-enedis/; *Germany:* Zhou and Brown (2017); *Italy*: Uribe-Pérez et al. (2016); *France, Italy, Germany* (number of households): Eurostat (2016); *Ontario:* Office of the Auditor General of Ontario (2014); *United Kingdom*: Department for Business, Energy and Industrial Strategy (2016), Office for National Statistics (2016); *United States*: U.S. Energy Information Administration (2017).

The objective of this report is aimed to explore the potential impact of real-time feedback based on smart meters on residential electricity demand. Section 2 provides background on smart meters, including describing the manner in which they can provide feedback to customers about electricity consumption and price, and the manner in which time-varying prices can be introduced under a smart metering system. Section 3 discusses how the impacts of smart meters and feedback technologies can be evaluated, using both experimental and observational methods. It also presents a literature review of prior studies focused on the impact of real-time feedback on residential electricity demand. Section 4 develops a simple model to explore how real-time feedback might affect residential electricity consumption. It shows that feedback could either increase or reduce electricity consumption, depending on the degree and type of perceptions held by the customer in the absence of information. Section 5 describes a case study in which real-time feedback was provided to residential customers in a quasi-random manner, in an electricity distribution area in Ontario, Canada. It evaluates the impact of real-time feedback on electricity consumption, explains how the effects of real-time feedback are determined, and shows how the impact of feedback varies by season, time of day, and outdoor temperature. Section 6 provides a number of concluding comments.

## 2. REAL-TIME FEEDBACK AND TIME-OF-USE ELECTRICITY PRICING

Smart meters differ in two important ways from traditional analogue electricity meters. First, they record electricity consumption using a digital, rather than analogue, technology. Electricity consumption on smart meters is also recorded with a corresponding time stamp, indicating time of use with hourly or higher frequency. On an analogue meter, in contrast, it is not possible to know when electricity was consumed within a billing period. Second, smart meter infrastructure allows communication between the meter and the electricity distribution company. This eliminates the requirement for manual in-place meter reading that is associated with analogue meters. Most smart meters additionally allow communication between the smart meter and the household. Figure 1 summarises the key differences between conventional and smart metering technology.

**Figure 1. Comparison of conventional (analogue) metering infrastructure and smart (digital) metering infrastructure**

| | Analogue meter | Smart meter |
|---|---|---|
| | | |
| *Measure* | Electricity over billing period | Electricity per hour (with time stamp) |
| *Communication* | None (manual reading) | Two-way communication |
| *Pricing* | No variation within period | Flexible |

These two differences between smart and conventional meters—regular recording of electricity consumption and communication ability—allow for important changes both in the way that electricity consumption is communicated to households, and in the way that electricity consumption is billed. The following sections discuss each of these potential changes. It is worth noting that when smart meters are adopted, households and their electricity distributors can make choices about using these features of smart meters or not. Upon adopting smart meters, certain jurisdictions and households have chosen not to change the way electricity is priced or to make use of feedback on household electricity consumption.

### 2.1 Smart meters allow real-time feedback on household electricity consumption

Like an analogue meter, a smart meter is installed outside the house, and does not typically display information on electricity consumption in an accessible, intuitive, or easy-to-read manner for the average household. On its own, then, a smart meter provides limited information to a household about electricity consumption. However, most smart meters include features to allow communication between the electricity meter and the household, typically using wireless technology. Using these features, or using near-real-time data relayed by the smart meter to the electricity distribution company, households can obtain

feedback on their electricity consumption.[3] The provision of this information may encourage households to change electricity consumption behaviour, possibly inducing energy conservation. There are a number of technologies that have been adopted to provide households with real-time information on their electricity consumption, outlined below.[4]

***Text message or e-mail***

Irregular text messages or e-mail messages can be used to highlight to consumers unusual consumption or changes in prices. For example, Gleerup et al. (2010) analyse a feedback scheme in Denmark in which e-mails or SMS messages are sent to participants when electricity consumption deviates from average levels by a pre-specified amount, and find a 3% reduction in electricity demand as a result.

***Internet site or mobile application***

It is possible to display information in a useful graphical format by linking a mobile app or internet website to the distribution company repository of consumption data. For example, Schleich et al. (2013) analyse an Austrian field trial in which consumers were provided with access to a website that displayed useful information relating to electricity consumption (with a one-day lag). They find limited impact of website feedback on consumer electricity demand.

***In-home display***

In-home displays use a wireless or optical reader to display information from the smart meter in a convenient and accessible manner to the household. Typical in-home displays feature graphics that display electricity consumption and price over the day and month, as well as indicators showing the current price of electricity. For example, Houde et al. (2013) analyse a programme that provided Google employees with an in-home display and find that electricity consumption was reduced by about 5% for several weeks following the receipt of the device.

## 2.2 Smart meters allow dynamic electricity pricing regimes

Smart meters record electricity consumption on an hourly or higher frequency and recording occurs with a time stamp. As a result, smart meters enable the electricity distribution utility to use prices that change over the course of a day, or change from one day to the next.[5] Changes in prices to reflect different costs of electricity provision over time are a market-based mechanism for encouraging energy conservation. There are a number of pricing schemes that are enabled through the use of smart meters. These schemes are described below and illustrated in Figure 2.

***Real-time pricing***

In a real-time pricing programme, residential consumers are exposed to the wholesale price of electricity. This can provide them with an incentive to conserve electricity during periods when demand is high or when supply is reduced. Real-time pricing is rarely applied for residential customers. Allcott

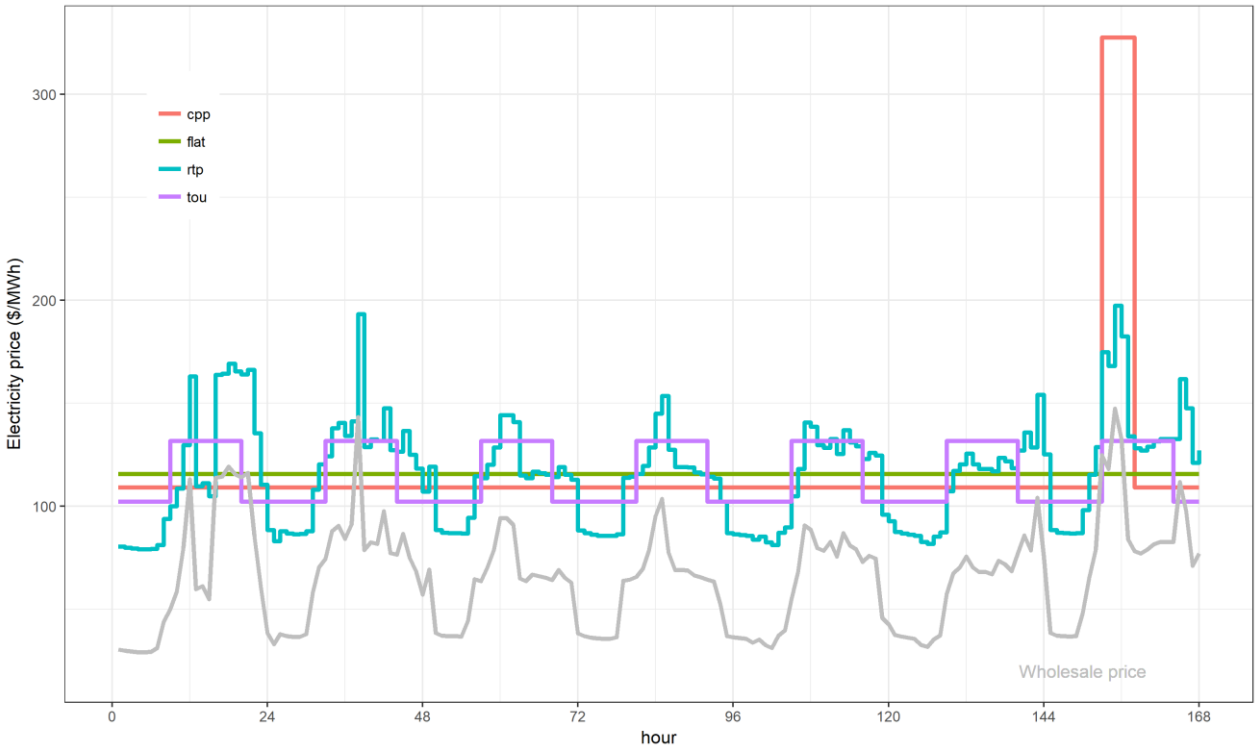
[3] While smart meters record electricity consumption on an hourly or higher frequency, they typically relay that information to the electric distribution company on a lower frequency, such as daily.

[4] It is important to note that there have been a number of efforts to supply households with feedback on their electricity consumption that do not rely on real-time consumption information (e.g. Allcott, 2011b; Fischer, 2008). This document focuses on real-time feedback.

[5] Prices that change over the course of a season are also possible with analogue meters.

(2011a) examines a case where selected Chicago consumers were exposed to real-time prices.[6] He finds a reduction in peak-period consumption and a welfare gain for consumers on real-time prices.

**Figure 2. Types of dynamic pricing systems for electricity, illustrated over a hypothetical one week (168 hour) period**




Note: Each tariff type recovers a premium over the wholesale price to cover electricity transmission and distribution expenses. A flat tariff does not change between days or hours. The real-time price (rtp) is based on a fixed mark-up over the wholesale price. The time-of-use (tou) price charges one price for on-peak hours (here, illustrated as 8 am to 7 pm) and a lower price for off-peak hours (here, 7 pm to 8 am). The critical peak period price (cpp) increases the residential price by a significant multiple during period of system stress (here, illustrated as a three-times price multiple).

### *Critical period pricing*

Under a critical period pricing tariff, customers pay a flat price for electricity except for during a certain number of "critical" periods during the year, when the consumer electricity rate increases substantially. These critical periods are times of particularly constrained supply, such as hot summer afternoons, when air conditioning demand peaks. The large increases in electricity price during a limited number of hours provide consumers with a substantial incentive to reduce demand during these periods. Jessoe and Rapson (2014) examine a critical peak period electricity scheme, and find that consumers indeed respond by reducing demand.

### *Time-of-use pricing*

In a time-of-use pricing scheme, the consumer electricity tariff changes by a predictable amount at predictable periods during the day. For example, during the summer season, a utility might declare the hours of noon to 7 pm on weekdays as "peak" periods, in which the price of electricity is double the price in other periods. Time-of-use pricing obtains some of the benefit of real-time pricing without exposing consumers to the fluctuating wholesale price of electricity.

[6] In the case examined by Allcott (2011a), consumers were exposed to the day-ahead forecast of the wholesale price.

# 3. EVALUATING THE IMPACTS OF REAL-TIME FEEDBACK ON ELECTRICITY DEMAND

## 3.1 Impact assessment methodologies

A significant body of research has gone into establishing the effectiveness of demand management strategies, such as real-time feedback technologies and dynamic electricity pricing, in increasing electricity conservation. This section provides a brief discussion of the methods used to derive causal inferences about the effectiveness of these alternative demand management strategies in changing consumer electricity demand.[7]

Two basic research designs are used to establish the impact of demand-side policy interventions in the electricity sector: *randomised controlled trials* and *observational studies*. In each case, the objective is to estimate the change in electricity demand due to an intervention.

**Box 1. Notation for impact evaluation of electricity conservation programs**

Some notation will be helpful in explaining the two types of research designs:

- $T_i$ is a dummy variable that indicates whether an individual is "treated," where the treatment involves being subject to a different electricity tariff or being provided with a feedback technology.
- $Y_i$ is the observed electricity consumption of person *i*.
- $Y^0_i$ indicates the potential electricity consumption of person *i* had he not been exposed to the treatment ($T_{it} = 0$), and
- $Y^1_i$ indicates the potential electricity consumption of person *i* had he been treated ($T_{it} = 1$).

***Randomised controlled trials***

Randomised control trials (RCTs) are increasingly used to assess the impact of conservation policies in the electricity sector – a number of RCTs are described in Section 3.2. The increased use of RCTs in the evaluation of relevant conservation policies is to some extent due to the more widespread use of smart meters, which allow for remote monitoring of changes in consumer behaviour.

In a typical RCT in this sector, participants are recruited from the population of households served by the electricity distribution company. Participants normally voluntarily self-select from the population, such that they may not be representative of the broader population.[8] This raises potential concerns about the external validity of an RCT — the degree to which the results will be valid for a different population — since participants in the RCT may not be representative of the population at large. There are few instances reported in which participants in an electricity conservation RCT are randomly selected from the broader population.[9]

Once households have been recruited to be participants in an RCT, they are randomly assigned to treatment and control groups. As is well understood, random assignment ensures that there is no systematic relationship between the observed or unobserved characteristics of respondents and their treatment status (Angrist and Pischke, 2008) — see Box 2 for more details. As a result, a simple

[7] A useful and general overview of issues associated with establishing causal inference is given in Angrist and Pischke (2008).

[8] It is important to distinguish the non-random *selection* of participants into an RCT from the random *assignment* of treatment to participants, which distinguishes RCTs from other research designs.

[9] One notable exception is Sexton et al. (1987), who randomly select participant households from the population (without asking for volunteers). Selected households were offered the possibility to withdraw from the program, but Sexton et al. (1987) report than "the actual refusal rate was negligible".

comparison of electricity consumption between treated and untreated households is an unbiased estimator of the effect of the impact of the treatment on electricity consumption.[10] The ease of drawing causal inferences has led to RCTs often being referred to as the "Gold Standard" for understanding the impact of interventions. In particular, the *internal validity*—the ability of a research design to recover an accurate estimate of the causal effect of treatment in the treated population—of well-designed and implemented RCTs is high.

**Box 2. Causal inference from RCTs**

The causal effect of the treatment on those who are treated (usually called the average treatment effect on the treated, or ATET) can be thought of as the expected difference in electricity consumption for a person *i* who is exposed to the policy intervention (or "treated"), compared to what the same person would have consumed if that person had not been exposed to the same policy (had she been "untreated"):

$$ATET = E\left[Y_i^1 \middle| T_i = 1\right] - E[Y_i^0 | T_i = 1].$$

Clearly, however, it is impossible to observe the same person at the same time being both treated and untreated. This is sometimes referred to as the *fundamental problem of causal inference*. Instead, in practice, researchers compare the observed – rather than potential – consumption of treated individuals to that of untreated individuals (possibly the same individuals, but at a different time): $[Y_i | T_i = 1] - E[Y_i | T_i = 0]$ .
It is possible to decompose this expression to see how it relates to the average treatment effect:

$$E[Y_i | T_i = 1] - E[Y_i | T_i = 0] = E\left[Y_i^1 \middle| T_i = 1\right] - E\left[Y_i^0 \middle| T_i = 1\right] + E\left[Y_i^0 \middle| T_i = 1\right] - E[Y_i^0 | T_i = 0]$$

The observed difference in average electricity consumption between treated and untreated individuals is the sum of two components:

- $E\left[Y_i^1 \middle| T_i = 1\right] - E\left[Y_i^0 \middle| T_i = 1\right]$: the difference due to the treatment, i.e. the ATET,
- $E\left[Y_i^0 \middle| T_i = 1\right] - E\left[Y_i^0 \middle| T_i = 0\right]$: the difference in average electricity consumption between treated and untreated individuals which is not due to the treatment, or selection bias.

In an RCT, treatment status is assigned by the experimenter and randomised across individuals. As such, there is no expected correlation between treatment status and individual characteristics, including pre-treatment electricity consumption. Formally, $E\left[Y_i^0 \middle| T_i = 1\right] = E[Y_i^0 | T_i = 0]$ implying that the expression above reduces to:

$$E[Y_i | T_i = 1] - E[Y_i | T_i = 0] = E\left[Y_i^1 \middle| T_i = 1\right] - E[Y_i^0 | T_i = 1]$$

In a randomised control trial, a comparison of electricity consumption between treated and untreated individuals is therefore an unbiased estimator of the effect of treatment both on treated individuals, and on the population at large, since these are randomly assigned and not different. The precision of the estimate can be improved by conditioning electricity consumption on observed household characteristics and/or on observed temporal demand shifters in a regression framework.

*Source*: Angrist and Pischke, 2008.

While most critiques of RCTs focus on external validity concerns relating to participant selection, there is another external validity concern that applies especially to RCTs known as the *Hawthorne effect*. The Hawthorne effect refers to the idea that participants in an experiment or other study change their behaviour as a result of being observed.[11] In a recent study of the potential for Hawthorne effects to arise in contexts related to electricity consumption, Schwartz et al. (2013) recruited households to a study and found that household electricity consumption falls by almost 3 percent even

[10] In practice, estimates of the impact of treatment on electricity consumption from an RCT typically use a regression-based approach which controls for factors other than treatment status. This can help to improve the precision of the impact of the treatment on electricity consumption.

[11] The Hawthorne effect derives its name from experiments relating indoor lighting to worker productivity conducted during the 1920s at the Western Electric Company's Hawthorne plant. Initial studies suggested that observed changes in worker productivity were not due to lighting, but instead due to the workers being observed. Subsequent studies using the same data have raised methodological issues that cast some doubt on this interpretation (Schwartz et al., 2013).

without any intervention aimed at promoting energy conservation, consistent with the idea of a Hawthorne effect. This should lead to some scepticism about the results of studies in which households are informed that they are participants in a study, as is the case in many of the studies that are described in the following section.

***Observational studies***

In an observational study, the treatment status of households is not selected by the analyst. Instead, household treatment is imposed by some other factor—either a choice by the household itself, by the policy maker or, more commonly in this context, by the electricity distribution company. This raises the possibility that household treatment status is correlated with observable or unobservable characteristics of the household, or with other observable or unobservable changes over time. As explained in Box 3, this can make it difficult to draw credible causal inference about the impact of treatment on electricity consumption using observable data.

**Box 3. Causal inference from observational studies**

In an observational study, the analyst is not in control of the treatment status of households or individuals, and as a result they are typically not assigned to treatment randomly. This raises the possibility of selection bias, whereby the observed difference in electricity consumption between treated and untreated individuals is related to pre-existing differences between these two groups. Formally, the selection bias term, defined in Box 2 as $E[Y_i^0|T_i = 1] - E[Y_i^0|T_i = 0]$, may not be equal to zero. To draw credible causal estimates from observational studies, it is important that the analyst provides evidence to support the assumption that there is no selection bias, i.e. that $E[Y_i^0|T_i = 1] = E[Y_i^0|T_i = 0]$. This guarantees that the average electricity consumption of the treated and untreated group is comparable prior to the introduction of the policy intervention.

Several empirical approaches have been used in an attempt to provide valid causal inference despite these potential problems (Greenstone and Gayer, 2009). These alternative methods are not systematically reviewed here; Angrist and Pischke (2008) provide a thorough discussion. In any case though, since observing the same household at the same time in both treatment and control states is impossible, estimating causal effects from an observational study rests on supporting evidence and the assumption that treated and control households are equivalent, after controlling for observable factors.

## 3.2 Findings from the literature on the effects of real-time feedback on electricity demand

This section briefly reviews the literature on the relationship between real-time feedback and consumer electricity demand, which mostly focuses on the residential sector. A more detailed summary of individual papers is provided in Appendix A. For a recent review of real-time pricing studies, see Faruqui and Sergici (2010).

Delmas et al. (2013) conduct a meta-analysis of 59 studies across multiple disciplines in the academic literature, all of which use RCTs to estimate the impact of information provision on electricity consumption. The study covers a wide variety of behavioural interventions that affect electricity demand, including real-time feedback, social norm comparisons, delayed feedback, audits, and other interventions. The results of the meta-analysis suggest that real-time feedback causes a reduction in electricity consumption of about 11 percent, on average. However, the authors caution that estimates of the effects of feedback are inflated in poor quality studies (for example, those that do not control for weather or other confounding factors). Across all types of feedback, they find that the treatment effect in high quality studies (which represent only a small fraction of all studies) is only about one quarter as large as the treatment effect for all studies. However, Delmas et al. (2013) neither provide an estimate of the effect of real-time pricing across high-quality studies in their data set, nor clarify whether they consider any of the real-time feedback studies in their survey to be high quality.

Faruqui et al. (2010) summarise findings from several pilot experiments using real-time electricity feedback, most of which were published in non-peer-reviewed outlets. The pilots use a number of different interventions, including different types of IHD, different types of payment for electricity, and different electricity tariffs, making it somewhat difficult to compare across studies. Faruqui et al. (2010) report that providing real-time feedback through an IHD to consumers is associated with a reduction in electricity demand of 3 to 13 percent. However, some of the reviewed pilot projects use very small samples, and the methods used to estimate the treatment effect and design the experiment are not clearly presented in the paper (owing to the large number of interventions surveyed), so it is difficult to ascertain the validity of the results.

In the last few years, several high-quality studies have been published that examine the effect of real-time feedback on consumer electricity demand. Gans et al. (2013) use a quasi-experimental approach based on the roll-out of smart meters with real-time feedback to a subset of Northern Irish households for this purpose. The context they examine, in which customers pre-pay for electricity and experience some of the highest electricity prices in Europe, is likely to produce large conservation impacts. They find that real-time feedback generates a large (11-17%) reduction in electricity consumption for treated households, which is sustained over several years. It is emphasised that these large impacts are likely context-specific.

Houde et al. (2013) report on a randomised controlled trial, in which real-time feedback on electricity consumption – with an IHD – was provided to a randomly assigned group of volunteering Google employees. They report a 5% reduction in electricity consumption due to the provision of an IHD, but find that the effect does not persist more than a few weeks. Again, the particular context of the study (Google employees) makes it difficult to understand how IHDs might affect consumption in a broader population.

Jessoe and Rapson (2014) examine the impact of providing an IHD in a context in which households are also exposed to critical peak period pricing (in which prices increase by 2-6 times for several hours at a time). They find that households with an IHD are significantly more responsive to critical peak prices than other households.

Harding and Lamarche (2016) analyse how the provision of real-time feedback technologies impacts consumer response to time-of-use (TOU) pricing. They find that households with IHDs do not significantly alter their profile of hourly electricity consumption compared to households without them in response to modest price changes.

In sum, the existing literature appears to consist of a fairly large number of studies of questionable quality, which finds varying but often large impacts of real-time feedback on electricity demand. More recently, several high quality studies have been produced, but while the internal validity of these studies appears to be high, it is not clear how well the results from these studies will transfer to other contexts because most have used rather idiosyncratic populations or treatments. As a result, there remains a relatively significant gap in the understanding of how real-time feedback affects electricity consumption.

## 4. ANALYTICAL FRAMEWORK

A simple model of consumer electricity demand provides general insights about the potential role of electricity feedback technologies. The model in this section assumes that consumers optimise electricity consumption decisions in response to perceived prices. As a result, it does not consider non-optimising responses, which could form part of the consumer response to IHDs. For example, if IHDs cause electricity consumption to become more 'visible' to the household, households may respond by conserving electricity independently of price changes. This response is not accounted in the model presented here. The model is static, which helps to capture the important features of the consumer problem related to feedback technologies. The model is based on a representative consumer, who chooses how much electricity and other goods to consume. However, since consumers do not consume electricity directly, but only as a result of the services it provides, electricity does not enter the consumer utility function directly. In the model, consumers choose between electricity services $s_t$ and a generic other good $x$ (the numeraire, with a price of one):

$$U = U(x, s_t).$$

Electricity services are differentiated according to the time they are consumed, $t$. For simplicity, the model considers a single energy service (differentiated by time), although the model could be easily extended to accommodate the more realistic scenario in which the consumer consumes multiple energy services. The consumer maximises utility subject to two constraints:

$$s_t = \eta e_t,$$

$$M = x + \sum_{t=1}^{T} p_t e_t.$$

The first constraint relates the demand for energy services (such as lighting, heating, refrigeration) to the consumption of electricity. The parameter $\eta$ reflects the energy efficiency of the electrical device. For example, an efficient LED lightbulb would have a larger value of $\eta$ than an incandescent lightbulb that delivered the same light output. Likewise, a better insulated house would have a larger value of $\eta$ than a less well insulated house, such that a given level of heating service could be provided with less energy input.

The second constraint is the consumer budget constraint, which ensures that total expenditures are equal to income ($M$). The constraint allows the price of electricity to vary over time.

With perfect information, the household optimises spending on electricity services as a function of prices, income, and the efficiency of the energy service technology. The optimal level of energy services is given then by the expression:

$$s_t^* = s_t^*(\eta, p_1, \dots, p_T, M),$$

where the asterisk indicates that this is the solution of the consumer maximisation problem. In practice, most consumers do not have perfect information relating to the consumption of electricity. Notably, most consumers likely have incomplete information about the relationship between the demand for energy services and the actual quantity of electricity consumed. Concretely, this means that they are unaware of how much electricity is required to power a given appliance. This is reflected in this model by the

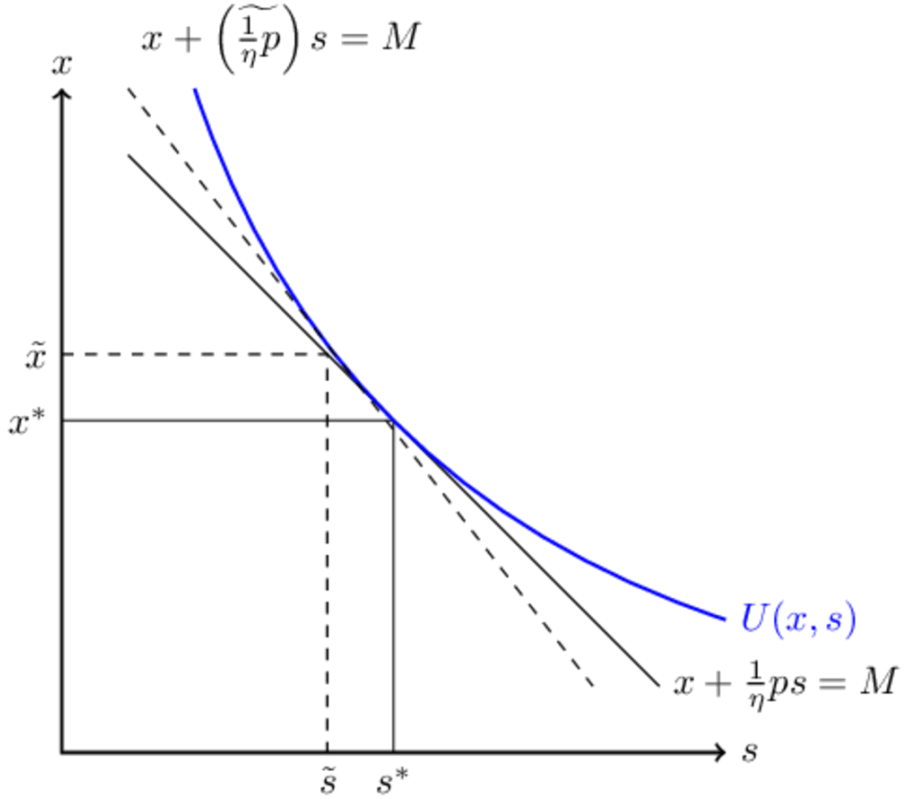
parameter $\eta$. In addition to this uncertainty, it is likely that most consumers are imperfectly informed about the price they face for electricity. As a result, consumers make decisions with imperfect information about these parameters.

A tilde is used to represent a parameter for which the consumer has imperfect information, such that consumer electric service demand under imperfect information is given by:

$$\tilde{s}_t^* = s_t^*(\tilde{\eta}, \tilde{p}_1, \dots, \tilde{p}_T, M)$$

The difference between $\tilde{s}_t^*$ and $s_t^*$ reflects the impact of imperfect information on consumer electricity demand. Depending on other sources of market failures that are present, this consumer misoptimisation is likely to carry a welfare cost. Figure 3 illustrates consumer misoptimisation as a result of imperfect information. In the figure, the time subscript for electricity consumption is eliminated, such that there are only two commodities consumed by the consumer—electricity services and other goods. Under perfect information, the consumer is able to choose the consumption of energy services and other goods to maximise utility. With imperfect information, the consumer misperceives the electricity price and/or the efficiency of electricity service provision (note that in this model, misperceptions about either of these values have identical effects). Importantly, this can result in electricity service demand (and thus electricity demand) that is either higher than or lower than optimal, depending on the direction of misperceptions about price and efficiency.

**Figure 3. Consumer utility maximisation under perfect vs. imperfect information**




The consumer utility function is defined over energy services ($s$) and other goods ($x$). With perfect information over prices and efficiency, the consumer chooses the bundle $(s^*, x^*)$. With imperfect information, the consumer chooses the bundle $(\tilde{s}^*, \tilde{x}^*)$.

The aim of providing real-time feedback on electricity consumption is to reduce the information imperfection and allow the consumer to better optimise over electricity consumption decisions. In particular, most real-time feedback technologies present the consumer with information about the price of electricity, reducing uncertainty over this aspect of the decision. In addition, real-time electricity feedback technologies provide information about real-time electricity consumption. With multiple energy service technologies, this does not completely resolve uncertainty about $\eta$, but it can narrow the range of uncertainty. Some feedback technologies do provide appliance-specific information about electricity consumption, which generates perfect information about $\eta$.

Smart electricity meters allow for the introduction of time-variant pricing such as dynamic pricing, critical period pricing, or time-of-use pricing, and it is important to consider the interaction of feedback technologies with these alternative pricing strategies. In particular, consider the response of a perfectly informed consumer to a change in the price of electricity at some time s, assuming that efficiency remains unaffected by the price change:

$$\frac{\partial \tilde{e}_t}{\partial p_s} = \zeta_{ts} = \frac{1}{\eta}\frac{\partial \tilde{s}_t}{\partial p_s}$$

It is possible to contrast this response with the effect of the same price change on an imperfectly-informed consumer. To do so, it is necessary to impose a particular structure on the uncertainty of the consumer with regard to the price of electricity. Here, it is assumed that the consumer knows the price of electricity with some error: $\tilde{p}_t = \delta_t p_t$. If the error $\delta_t$ is greater than one, the consumer perceives electricity prices to be higher than they actually are, whereas if the error is smaller than one, the consumer perceives electricity prices to be lower than they actually are. As a result, the change in demand for an imperfectly informed consumer following a change in the price of electricity at time *t* is:

$$\frac{\partial \tilde{e}_t}{\partial p_s} = \delta_t \zeta_{ts}$$

With this error structure, the responsiveness of the electricity consumer to a change in price can be either lower or greater than the responsiveness of a perfectly informed consumer. In particular, an electricity consumer that systematically believes electricity prices are higher than they actually are will over-respond to a change in electricity prices, and vice versa. However, alternative structures of the function for the perception of electricity prices result in different predictions. For example, an error structure $\tilde{p}_t = p_t + \delta_t^A$ results in an imperfectly informed consumer that responds identically to a price change with a perfectly informed consumer (here, $\delta^A$ is an additive error term). In contrast, a consumer that is completely misinformed about electricity prices, such that $\tilde{p}_t = \delta_t^C$ will not respond at all to a change in electricity prices (here, $\delta^C$ reflects a belief about electricity prices that is independent of actual prices).

Once again, the role of electricity feedback technologies is to provide improved information to the consumer, in part about electricity prices. Depending on the type and degree of misperception of energy prices by the consumer, the provision of feedback technologies can result in more or less price responsiveness by consumers.

## 5. A CASE STUDY—MEASURING THE EFFECT OF FEEDBACK TECHNOLOGIES IN ONTARIO, CANADA

This section presents a case study on the implementation of time-of-use electricity rates and in-home real-time electricity feedback technologies. The results and analysis presented in this section are based on the paper by Martin and Rivers (2015), which provides a more detailed discussion.

The case study presents an evaluation of a natural experiment in which in-home electricity displays are rolled out quasi-randomly to about 7000 households served by a electricity distribution company in Ontario, Canada. This section first describes the context in which the programme was offered. It then describes the empirical approach used for understanding the causal effect of real-time feedback on household electricity consumption. Finally, it presents the results of the analysis.

### 5.1 Context

Households within the service area of an Eastern Ontario local electric distribution company (EDC) were offered the opportunity to participate in peaksaverPLUS, a demand response programme. Upon agreeing to participate in the programme, the EDC activates a device on the home's electric hot water heater that allows the utility to remotely reduce the electricity consumption of the water heater during certain high-demand periods of the year (for up to four hours at a time and only between May and October).[12]

It is important to emphasise that the pre-condition for programme participation is ownership of an electric hot water heater. Since there is a very strong correlation between owning an electric hot water heater and using electricity as the primary space heating energy source (i.e. baseboard heaters), it is likely that the vast majority of the households in the sample primarily use electricity for both space and hot water heating.[13] The effect of real-time feedback on electricity consumption shown estimated in the report should therefore be interpreted as the effect of feedback on households with electric heat and hot water. In addition, it is important to emphasize that households that participate in the program are not randomly drawn from the population, but instead select into the demand response program. The statistical implications of this selection are addressed below, but here it is important to emphasize that the results obtained in this paper reflect the subset of households with electric water heaters that select into a demand response program. It is not clear how generalizable the results are to the full population, since demographic information on households was not available for this study.

***In-home display***

In return for participating in the demand response programme, participating households received an in-home real-time electricity display (IHD). The IHD is wirelessly connected to the house's digital electricity meter (all Ontario households have been converted from analogue to digital electricity meters). It displays, in real time, the power consumption by the household in physical units (in kW), the current retail electricity price (in $/kWh), and the implied current expenditure on electricity (in $/day). It also

[12] For a household to be eligible for the programme it must have an electric hot water heater. During the two-year period covered by the data, the utility only implemented load control events for two four-hour periods. Because this report focuses on the response to real-time feedback and not the response to the load control interventions, days on which loads are controlled are removed from the sample. Load control events were declared by the Ontario Power Authority on June 24 and July 16, 2013, from 2 pm to 6 pm.

[13] Using a separate data set—the US Residential Energy Consumption Survey—shows that single family households with electric hot water heaters have roughly an 80% probability of also using electricity for space heat.

shows the consumption of electricity over the previous 24 hours as well as over the previous month. Additionally, the IHD is equipped with an LED display, which glows a different colour depending on the current electricity price (e.g., green is off-peak; yellow is mid-peak; red is on-peak). Figure 4 is a picture of the IHD used in this study.

**Figure 4. In-home electricity display used in the field experiment**

*Source: Aztech.*
Note: Two of the different displays possible are shown. The top LED bar glows a different colour depending on the current electricity pricing period.

The IHDs were sent from the utility by mail to each participating household, with instructions for activation. The utility had already pre-paired each IHD with the electric meter at the residence so that upon receiving the IHD the household could activate the device simply by plugging it in to a standard electrical outlet (information on electricity consumption is then transferred wirelessly from the digital electricity meter to the IHD). The data indicates the date that the device was couriered to the customer, and this date is used as the start of the "treatment effect" associated with the IHD. It is important to note that there is no way of knowing if or when the consumer actually installs the IHD, and so the effect that estimated throughout the report is an intent-to-treat effect, rather than a treatment-on-the-treated effect. The intent-to-treat effect is a lower bound on the treatment-on-the-treated effect.

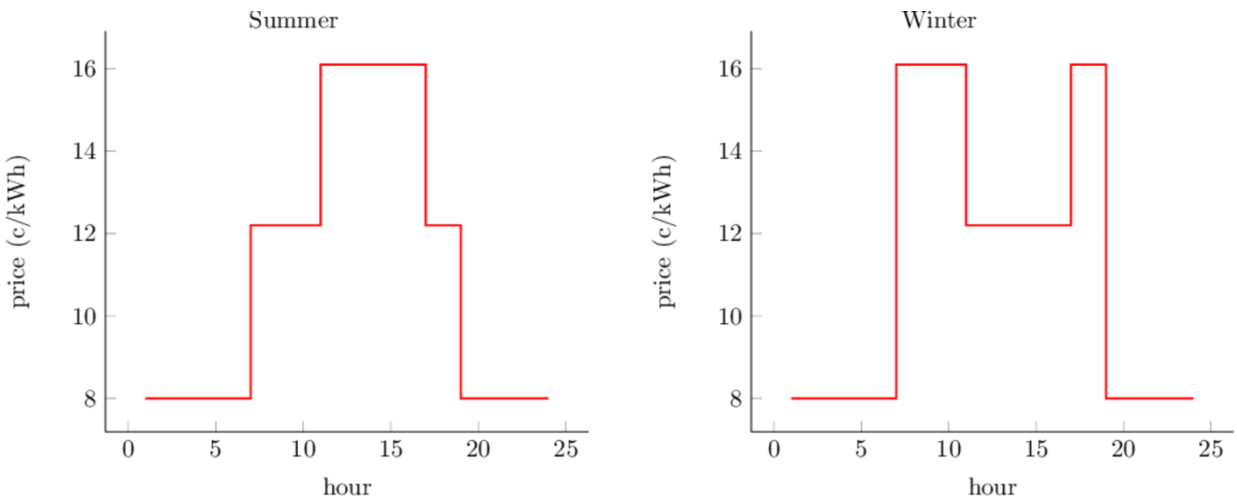
### *Time-of-use electricity prices*

In the Electricity Restructuring Act, 2004, the Ontario Energy Board (OEB) was mandated to implement a regulated price plan that included a TOU pricing structure in order to more accurately convey the real costs of generation to consumers, and to encourage customers to shift demand away from peak periods. It is one of the only jurisdictions in the world (the other is Italy) to implement smart meters for all residential customers as well as an associated TOU pricing plan (Faruqui and Lessem, 2014). The roll-out of the smart meters and implementation of the TOU pricing plan were complete prior to the beginning of the period covered by this study.[14]

[14] See www.ontarioenergyboard.ca/OEB/Industry/Regulatory+Proceedings/Policy+Initiatives+and+Consultations/Smart+Metering+Initiative+(SMI)/Smart+Meter+Deployment+Reporting. Roll out of smart meters to Ontario residential customers was monitored by the Ontario Energy Board in monthly progress reports until June of 2012, at which point 99% of eligible customers had smart meters installed. Some Electric Distribution Companies in Ontario implemented time of use pricing as early as 2009, and all EDCs had implemented time of use pricing by 2012. This study uses data from the period September 2012 to 2014.

Ontario's TOU pricing structure divides each hour into one of three blocks representing off-peak, mid-peak, or on-peak periods. Weekends and holidays are off-peak periods, as are the hours from 7pm to 7am each weekday. In the summer, hours from 7 am to 11 am and 5 pm to 7 pm are mid-peak, while hours from 11 am to 5 pm are on-peak.[15] In the winter, the daytime blocks are switched, such that peak periods are during the morning and evening, while the mid-peak period is from 11 am to 5 pm. The weekday time of use prices as of September 2015 are shown in Figure 5.

**Figure 5. Weekday time of use pricing periods by hour of the day in Ontario**




Note: Prices are for September 2015. The prices shown are for electricity generation only, and do not cover other components of the electricity bill related to e.g. transmission and delivery.

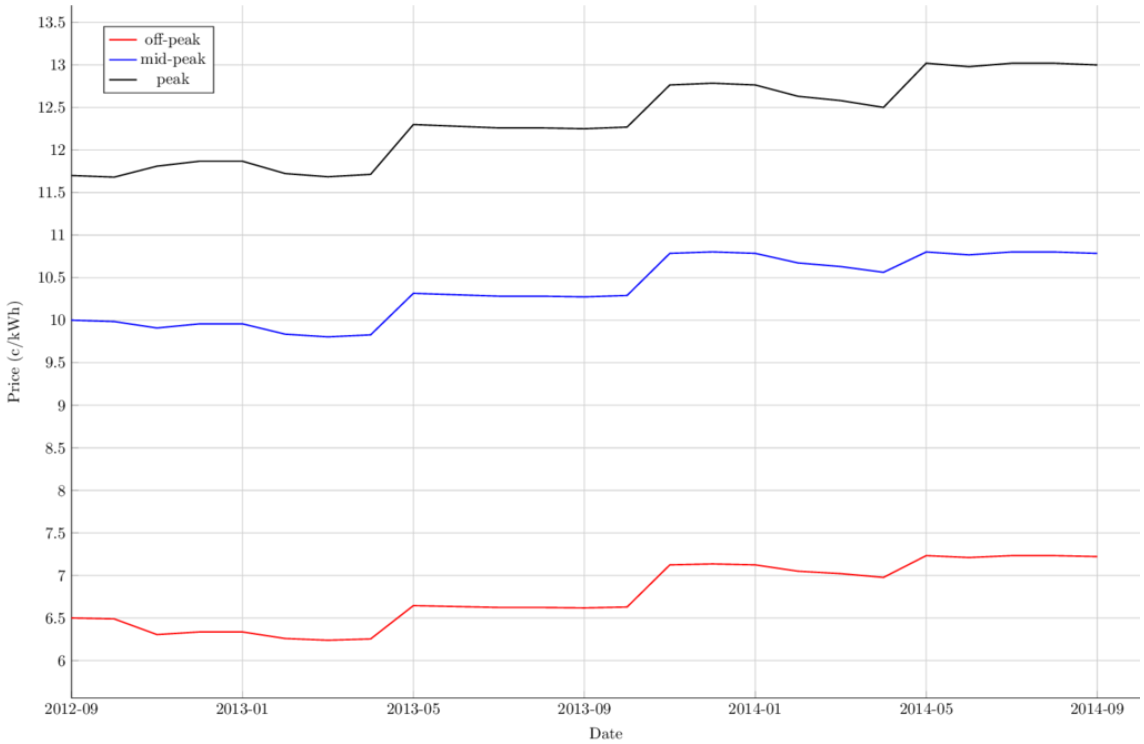
Data source: Independent Electricity System Operator, Ontario

The OEB adjusts TOU prices every six months in response to changes in electricity load as well as the profile of electricity generators in the province. Figure 6 shows the prices for each block observed in the study period (all prices are deflated by the Ontario Consumer Price Index). Real electricity prices have been trending upwards in Ontario during the study period. The ratio of peak/off-peak prices has changed slightly during the study period, but has remained between about 1.5 and 2.[16]

[15] Summer is defined as the months from May to October.

[16] As in most utilities, the cost of the electricity commodity is just one component of the electricity bill received by the customer. Customers also pay a charge for delivery of electricity, as well as a regulatory charge, debt retirement charge, and a service charge. Some of these additional charges scale with usage, while others are fixed. In total, the all-in electricity price varies less over price blocks than the electricity commodity charge. Figure 5 illustrates the electricity commodity charge only.

**Figure 6. Time of use prices during the study period**




Note: Prices are corrected for inflation using the Ontario Consumer Price Index. The prices shown are for electricity generation only, and do not cover other components of the electricity bill related to e.g. transmission and delivery.

Data source: Independent Electricity System Operator, Ontario

## 5.2 Research design

The impact of IHDs on electricity consumption is estimated by making use of the staged roll-out of IHDs to electricity consumers. In particular, the impact of the IHD on electricity consumption is determined by comparing a household that has just received an IHD with the same household just before receipt of the IHD, and controlling for unobserved confounders using households that are just about to receive an IHD as a control group. Both of these households are programme participants, and so are likely similar in important respects (at minimum, both have electric hot water heaters, and likely have electric space heaters, for reasons discussed in the prior section).

The research design imposes the assumption that households that are enrolled in the IHD program early in the year are equivalent to those that are enrolled in the programme later in the year. The identification approach might be compromised if these two types of households are significantly different. There are two reasons to think that the assumption is likely to be valid. First, although the roll-out of IHDs is long enough to exploit it for empirical purposes, from a household's perspective it is still relatively short; there is no reason to think that there is a significant difference between a household that enrols in a demand response programme a few months before another household. Second, the phased roll-out was in part a response to resource constraints at the utility and this provides a source of exogenous variation in adoption date that is exploited in the analysis.

In addition to these qualitative arguments that suggest the timing of the roll-out is exogenous, it is possible to provide quantitative evidence. To do this, observations of electricity consumption prior to any households receiving an IHD are used (IHD roll-out began in January 2013, and the data on electricity consumption starts in September 2012). A comparison between pre-programme electricity consumption in these households is used to determine if there is any difference between early adopting and late adopting

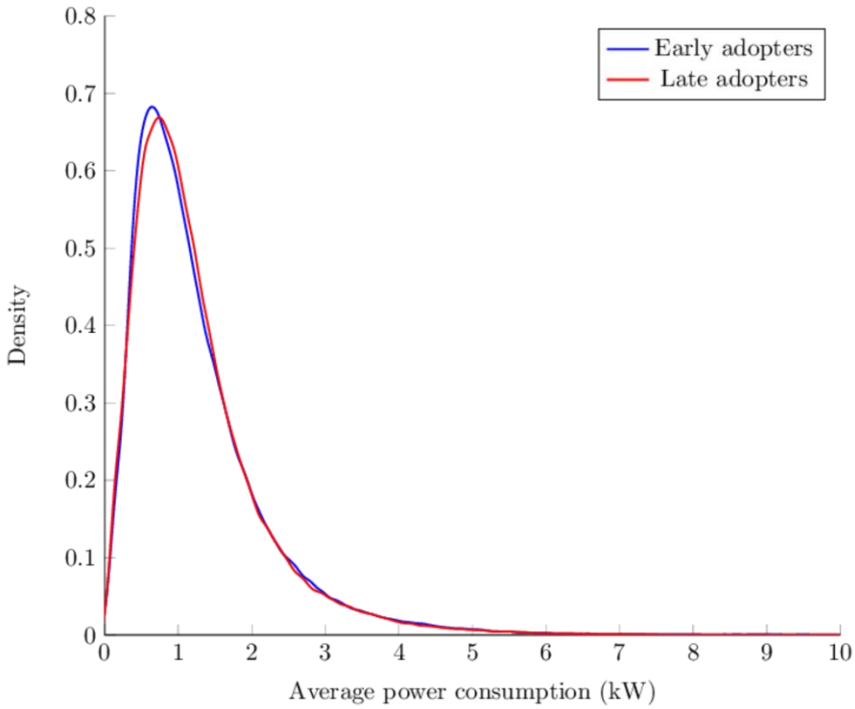
households that could contaminate the estimated treatment effects. To operationalise this, the data are split into two groups: early adopters and late adopters. Households are split according the median date of adoption (August 21, 2013). Pre-programme electricity consumption in early and later adopters is then compared. Figure 7 shows the results of this comparison graphically. Daily electricity consumption is clearly very similar between early- adopting and late-adopting households in the pre-treatment period, following the qualitative arguments above. Additional evidence on this point comes from a regression of pre-programme electricity consumption on the date of IHD receipt. There is no statistical relationship between these two variables. Martin and Rivers (2015) provide more formal statistical evidence that pre-treatment consumption in early-adopting and late-adopting households is identical.

### 5.3 Findings

The main finding of the analysis is that households reduce electricity demand by an average of about 3% once they receive an in-home display (the result is "statistically significantly" different from zero at conventional significance levels). As described in the following, this reduction in electricity demand is maintained for at least several months following receipt of the device. The result is estimated based on a comparison of daily household electricity consumption within the same household before and after receiving an IHD, and controlling for temporal shifts in electricity consumption experienced by all households in the small service area of the utility, for example due to holidays or changes in weather. The average effect is similar when controlling for household-by season fixed effects, and also when hourly rather than daily data is employed for estimation. Tables showing this result and others in this section are provided in the appendix, and more detail is available in Martin and Rivers (2015).

**Figure 7. Density of daily electricity consumption in pre-treatment period (September to December, 2012) for participating households**

Average power consumption (kW)




Note: The 'early' line includes households that received an IHD prior to August 13, 2013, and the 'late' line includes households that received an IHD after August 13, 2013.
Data source: Author's calculations.

**Box 4. Quasi-experimental research design**

To estimate the effect of IHDs on the average consumption of electricity ($Y_{it}$), Martin and Rivers (2015) conduct a regression of the log of electricity consumption on a dummy variable that indicates that the household has received an IHD, as follows:

$$\log(Y_{it}) = \alpha + \beta IHD_{it} + \mu_i + \lambda_t + \epsilon_{it}$$

The IHD dummy variable takes on a value of one on all days on and subsequent to the date that the household receives the IHD, and takes on a value of zero on all days prior to receipt of the IHD. The specification includes household fixed effects, $\mu_i$, to account for unobserved and observed heterogeneity between households. Given the bias that can be induced from not properly controlling for demographic effects (Delmas et al., 2013), it is important to control for household effects. The regression also includes time fixed effects $\lambda_t$, to account for temporal shocks that affect electricity demand. There are roughly 2 years of hourly data (2 years × 8760 hours per year ≈ 17 500 hours) reflecting about 17 500 hours, so there are roughly this number of time dummy variables in the model. All households in the data are in the service area of a single EDC (with a small service area of about 60 km$^2$) and so experience the same average weather and other time-varying disturbances. Because electricity prices change for all households simultaneously, the time fixed effects also absorb any impact of changing electricity prices on average household electricity demand. The coefficient β then indicates the difference in average log electricity consumption conditional on being treated with an IHD.

As described above, the identification of the $\beta$ coefficient leverages the quasi-experimental roll-out of the IHDs to consumers. Statistical evidence supporting the exogeneity of the roll-out is described above, and additional evidence is provided in Martin and Rivers (2015). To ensure validity of the estimates, only households that eventually receive an IHD are included in the estimation.

In addition this this base specification, Martin and Rivers (2015) also reports on the results of specifications in which household-by-season fixed effects are included, to account for potential seasonal heterogeneity in household consumption that varies by household and might be correlated with IHD adoption. Including these additional fixed effects does not significantly alter the overall results.

This section also reports on the results of several specifications in which the IHD dummy variable is interacted with time-of-day dummy variables, with outdoor temperature, with electricity prices, and with other variables, to understand how the effect of having an IHD varies over various margins.

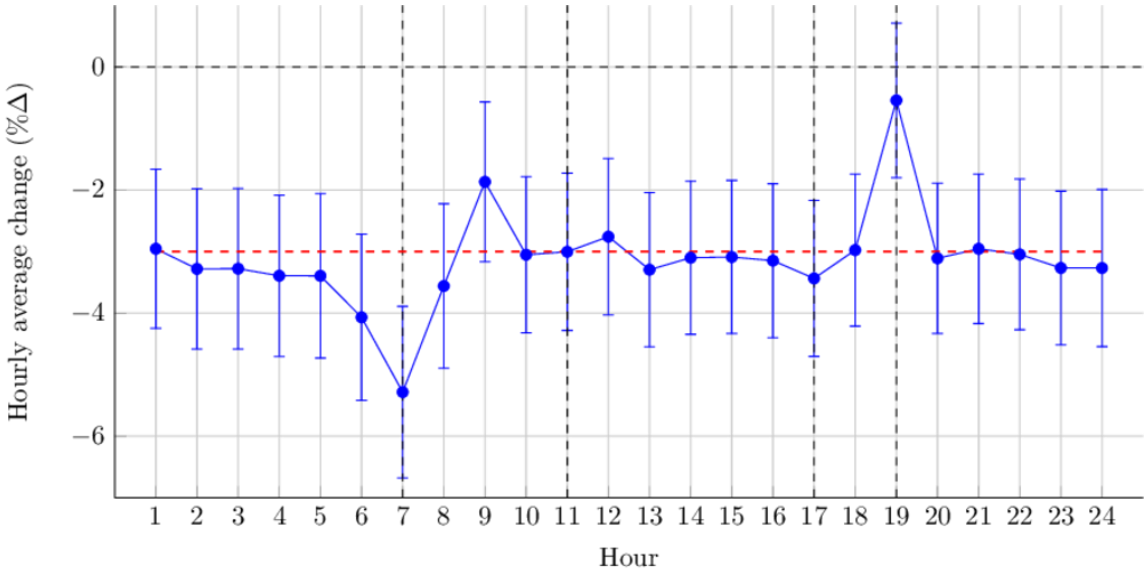
In all instances, standard errors are clustered at the household level. This accommodates potential correlation in electricity consumption over time within a household.

*Sources*: Delmas et al. (2013); Martin and Rivers (2015).

### *Temporal variation in household response*

The hourly metering data produced by smart meters in Ontario allows for the possibility of breaking down the response by hour of the day. This is done in Figure 8. The figure indicates that for most hours of the day, the hourly effect of an IHD is very similar to the average effect over all hours of the day (indicated by the dashed red line). In fact, the hourly effect is only statistically different from the average effect for two hours of the day: the hour up to 7 am and the hour up to 7 pm. This is notable for two reasons. First, the stability in the effect across all hours of the day suggests that households are not dynamically responding to real-time information over all hours in the day, but rather are permanently adjusting behaviour in a way that generates a relatively uniform response across hours of the day. Second, the result provides preliminary evidence that changes in the time-of-use price within a day are not driving major changes in the response to the IHD (a point explored further below). In particular, the largest reduction in electricity demand is in the hour leading up to 7 am, which is on off-peak price. The smallest response is in the hour leading up to 7 pm, which is on mid-peak or on-peak price, depending on the season.

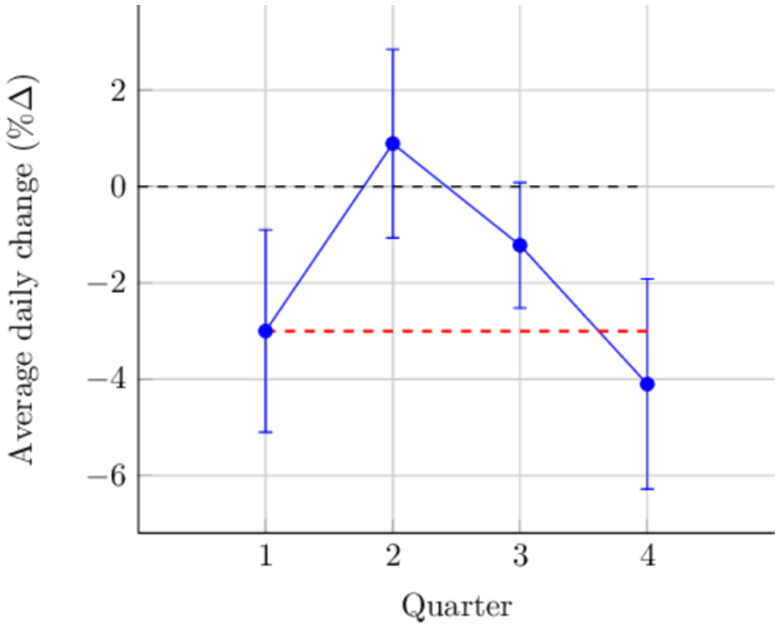
**Figure 8. Change in hourly electricity consumption due to receipt of in-home electricity display**




Note: Hours reflect all consumption up to that hour; so hour 8 is electricity consumption from 7:01am to 8:00 am, for example. Dashed black lines delineate pricing blocks. The dashed red line indicates the average effect over all hours of the day.
Data source: Author's calculations.

While Figure 8 breaks down the response according to the hour of the day, Figure 9 breaks down the response according to season of the year. Unlike the relatively flat response over the course of the day, Figure 9 shows that there is a distinctive seasonal effect of the IHD on consumption. In particular, during the spring and summer months, there is a small and statistically insignificant impact of the IHD on electricity consumption. In contrast, during the winter and fall heating seasons, the IHD causes a roughly 4 percent reduction in the demand for electricity. This is suggestive evidence that households respond to the IHD in part by reducing the demand for space heating. Further evidence on this point is provided in the following section.

**Figure 9. Results by quarter of the year with 95% confidence interval**

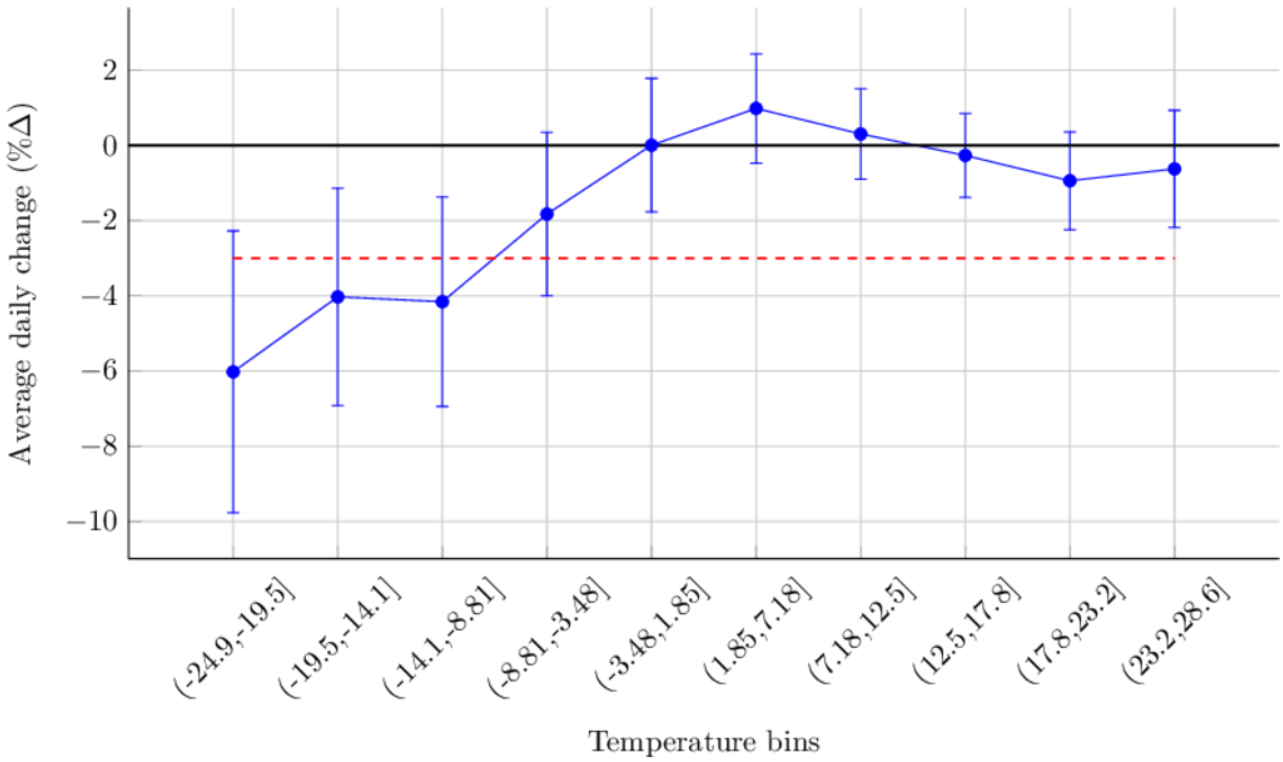



Note: Quarter 1 is January-March and so on. The dashed red line indicates the average effect over all seasons.
Data source: Author's calculations.

***Household response by outdoor temperature***

To provide additional evidence on the mechanism through which households are responding to the IHD, Figure 10 conducts a regression in which the hourly outdoor temperature is interacted with the IHD dummy variable. Temperature is divided into equally-sized bins that span the range of temperatures in the data set, in order to enable visualisation of the potentially non-linear relationship between outdoor temperature and the impact of the IHD. This enables the possibility of establishing whether the presence of an IHD produces a differential response at different outdoor temperatures, and helps to establish the mechanism by which households respond to the IHD.

**Figure 10. Treatment effect by temperature bin (hourly), 90% confidence intervals**




Note: The dashed red line indicates the average effect over all temperatures.
Data source: Author's calculations.

The figure shows that when the outdoor temperature is low, the presence of an IHD results in a significant reduction in electricity consumption. In particular, at an outdoor temperature of -8°C or below, household electricity consumption is reduced by 4 to 6 percent due to the presence of an IHD (with the larger reduction at lower temperatures). The effect of the IHD on electricity consumption declines near-monotonically as temperature increases until the outdoor temperature is between 2°C and 7°C, at which point the IHD appears to have no effect on electricity demand. At temperatures above 17°C, there is weak evidence that the IHD reduces household electricity demand.

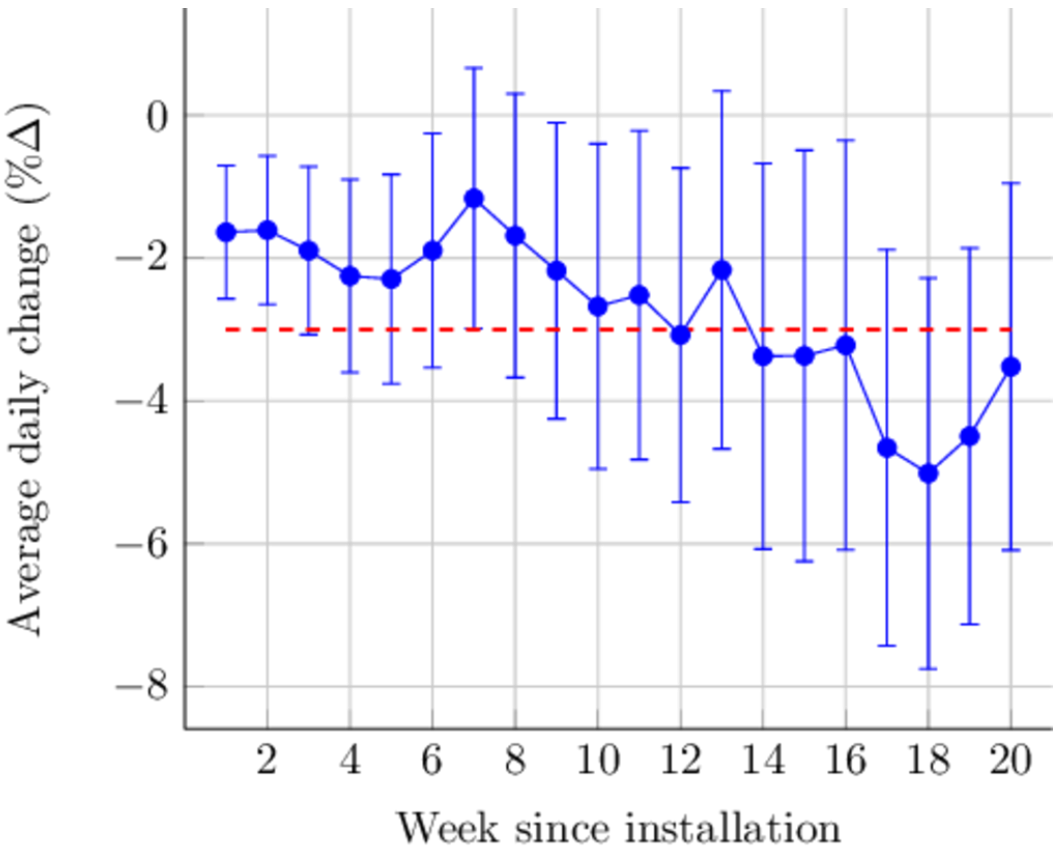
The figure provides additional evidence that households respond to receiving an IHD by adjusting thermostat setpoint. When temperatures are extremely cold, suggesting a large heating load, the effect of the IHD is larger. Similarly, when temperatures are extremely hot, there is some evidence that households with an IHD consume less energy than households without. In contrast, when temperatures are less extreme, such that there is little requirement for heating or cooling, the IHD does not appear to have any effect on electricity consumption.

It is possible to make an estimate of the shift in thermostat setpoint that would give rise to the effects observed in this study. To provide an estimate, the HOT2000 building simulation model that is developed by Natural Resources Canada is used to simulate household heating requirements for different indoor temperature setpoints and outdoor temperatures. Based on model simulations with different indoor setpoints and based on weather in Ontario, a 1°C reduction in the indoor temperature setpoint is estimated to reduce building energy consumption by about 4 percent during the heating season. The US Department of Energy suggests a reduction of 0.6 degrees Celsius (1 degree Fahrenheit) is sufficient to reduce energy consumption by about 3 percent.[17] These two studies suggest that a possible interpretation of the findings here is that households responded to an IHD by reducing the thermostat setpoint by about 1°C or slightly less.

***Persistence of household response***

To establish whether IHDs can be (part of) a cost effective strategy to encourage households to reduce their electricity consumption, it is critical to know whether the impact of the IHD on consumption is transitory or persistent. Prior studies have shed some light on this (e.g. Gans et al., 2013; Houde et al. 2013), but many have not followed households for sufficiently long periods to observe whether the response is transitory or persistent.

**Figure 11. Persistence of IHD treatment effect by week of treatment, 90% confidence intervals**




Note: The dashed red line indicates the average effect over all weeks.
Data source: Author's calculations

[17] See http://energy.gov/energysaver/thermostats.

Figure 11 presents the results of a regression in which the IHD treatment dummy is interacted with a variable indicating the number of weeks since the IHD has been received. As above, bins are used to enable the identification of a possibly non-linear response. Figure 11 shows that the effect of the IHD appears to increase over time, from roughly 2 percent upon initial receipt to around 4 percent after households have had the IHD for several months. Importantly, the effect of the IHD on electricity consumption does not appear to be transitory, but rather appears to increase fairly steadily over the five-month period over which households are observed following receipt of the IHD. Although it is again not possible to pin down the precise mechanism explaining this response, it is plausibly linked to the increased salience of electricity consumption under IHD adoption, leading consumers to shift habits in a persistent manner, for example by acquiring more energy efficient appliances or by permanently adjusting thermostat setpoints.

***Real-time feedback and time of use electricity prices***

The programme under study is in Ontario, a province with time-of-use electricity pricing for nearly all residential customers. Time-of-use prices in Ontario are provided in Figures 5 and 6. During the period covered by the data, on-peak prices for electricity were about twice as high as off-peak prices. During the period covered by the data and the rollout of IHDs to customers, the time-of-use tariff for residential households changed twice: once in Spring 2013 when it switched from the winter to summer tariff structure, and once in Fall 2013 when it switched from summer to winter structure. At each switch, prices for electricity were also increased for each block of electricity. It is possible to use these two tariff changes to identify the impact of changes in electricity prices on electricity consumption, both for households with an IHD as well as for households that have yet to receive an IHD. As explained in Section 3 above, it is theoretically not clear whether households with real-time feedback should respond more or less to a price change than households without real-time feedback.

For households without an IHD, the estimated short-run elasticity of electricity demand with respect to price is between -0.17 and -0.37, depending on the time period and the model specification. This is well within the range of other estimates of the short-run elasticity for electricity demand Lijesen (2007). For households with an IHD, the estimated elasticity of demand is about -0.2, and does not change appreciably across different time periods. Interestingly, this implies that the elasticity estimated for households with an IHD is sometimes higher and sometimes lower than that estimated for households without an IHD. It is therefore not possible based on this study to conclude that real-time feedback appreciably increases or reduces the sensitivity to time-of-use electricity prices.

## 6. CONCLUSIONS

This report summarises the empirical literature on the effect of real-time feedback on electricity consumption decisions, presents a simple analytical model that describes how an optimising consumer responds to real-time feedback, and presents results from an empirical study based on a large-scale roll-out of IHDs to electric utility customers in Canada. Taken together, the results suggest that real-time feedback is likely to cause consumers to reduce electricity consumption. The results also suggest that consumers are unlikely to shift patterns of electricity consumption (i.e., the timing of electricity demand throughout the day) substantially in response to receiving an IHD if differences in prices throughout the day are modest. Finally, the results suggest that household respond to receiving real-time information on electricity price and consumption in part by making one-time decisions of a durable nature—such as adjusting thermostat setpoints, hot water heater settings, or upgrading the energy efficiency of household equipment—rather than by responding in real-time to the real-time information.

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## APPENDIX: INVENTORY OF STUDIES ON THE IMPACTS OF REAL-TIME FEEDBACK ON ELECTRICITY DEMAND

**Allen and Janda (2006)–Oberlin, Ohio** Between January and March 2006, 60 Oberlin households were surveyed to better understand the effects of continuous feedback in a residential setting across socioeconomic groups. 10 of the 60 surveyed households were randomly se- lected into the treatment group, while the remaining 50 served as the control group. The sample consisted of 30 households from the low-income section of Oberlin and 30 house- holds from the high-income section. Energy Detective electricity monitors, which display both real-time and historical electricity consumption in kilowatt hours or dollars, were given to the treatment group. Baseline data was also collected from the households using utility bill records and semi-structured interviews.

*Impacts*: Researchers found no statistically significant difference in electricity consumption between the treatment and control groups.

**Commission for Energy Regulation (2011)–Ireland** Electric Ireland's Customer Behaviour Trial aimed to gauge customer response to various time-of-use tariffs and demand side management stimuli (enabling technologies) between January and December 2010. A benchmark baseline data collection period was held between July and December 2009, just prior to which time meters were installed in all 5028 participating households. Participants were assigned to treatment and control groups, with the former receiving various combinations of time-of-use tariffs, in-home displays, and fridge magnets and stickers that outlined different electricity use time bands and cost per band.

*Impacts*: Participants equipped with in-home displays reduced their overall energy consumption by an average of 3.2 percent and their peak demand by 11.3 percent.

**Delmas et al. (2013)–Meta-analysis** The authors conducted a meta-analysis of 59 experimental studies, conducted between 1975 and 2012, on the impacts of information-based conservation strategies on energy consumption. 22 percent of the included studies were explicitly on the effects of real-time feedback and related enabling technologies such as energy monitors or in-home displays. A strict set of selection criteria were employed in the vetting of relevant studies. Included papers met quality standards (i.e., were peer reviewed), had experimental designs, were only related to feedback effects in the residential sphere, and reported feedback effects in percentage relative to a baseline or in kilowatt hours. Finally, all studies were run through a meta-regression analysis to estimate the effects of various conservation strategies.

*Impacts*: On average, real-time feedback elicited an 11 percent reduction in energy consumption. Additionally, researchers found a weighted average energy conservation of 7.4 percent for all information strategies.

**Karkkainen (2004)–Denmark and Norway** EFFLOCOM (Energy efficiency and load curve impacts of commercial development in competitive markets) report summarises results from several energy efficiency pilot projects conducted in the EU and Norway, with the aim of understanding market barriers to energy efficiency. The Danish pilot—held between October 2003 and January 2004—consisted of 25 households equipped with "Amlight" load control devices that controlled the energy use of several appliances. The first Norwegian pilot was a mixed commercial/residential pilot in Oslo between January 1998 and December 2001. During the pilot 173 residential and 40 commercial participants were provided "smart thermostats," allowing them to control electric heating and boilers. From August 2003 to May 2004 a second residential/commercial Norwegian pilot was held outside of Oslo with a sample of 10,894 treatment and control group members. Customers were provided "Ebox" load control relays, which

allowed for direct two-way communication of consumption data between electricity users and producers via the internet.

*Impacts*: Participants in the Danish pilot saw peak demand reductions of approximately 2.5 to 5.3 kW/house. Residential customers in the first Norwegian pilot reduced peak demand by 8.8 to 10.7 percent, while commercial customers reduced their peak demand by an average of 8 percent. The second Norwegian pilot realised an average peak demand reduction of 11 percent.

**Faruqui and George (2005)–California** California's Statewide Pricing Pilot was conducted between June 2003 and December 2004, involving approximately 2,500 residential and small- to-medium size commercial and industrial customers of three investor-owned utilities. The chief aim of the pilot was to demonstrate whether or not customers reduce energy consumption in response to time-varying prices, but it also contained evidence on the impacts of real-time energy monitors. A subsection of the sample was recruited from the general population and was given the choice of having smart thermostats installed, while another subsection already had smart thermostats from a previous pilot.

*Impacts*: Customers who received the Critical Peak Pricing (CPP) rate intervention saw peak electricity use reductions between the 8 to 15 percent. However, when smart thermostats were added to the CPP intervention, the peak reductions were even greater, at 25 to 30 percent.

**Faruqui and George (2005)–Baltimore, Maryland** Over the summer of 2008, Baltimore Gas & Electric ran their Smart Energy Pricing Pilot, which tested the effects of an IHD called the "Energy Orb" (i.e., spheres that change colour in real-time depending on energy usage) in a residential setting. The pilot also used several pricing structures such as flat, seasonal, and volumetric rates and educational materials. A subsection of the 1,021 household sample received the IHD, while 354 customers comprised the control group. There was no indication of whether or not all of the sample customers were randomly selected or if treatment was randomly assigned to participants.

*Impacts*: With educational materials and different rate structures alone, the study found between 18 to 21 percent reduction in critical peak electricity demand. When the Energy Orb was combined with the dynamic pricing programmes, the reduction in critical peak demand was in the 23 to 27 percent range.

**Faruqui et al. (2010)–Various locations** Authors present a survey of evidence from twelve experimental pilot programmes, some ongoing during the time of writing, in both North America and international locations. The study intended to extract some approximations of the impact of IHD real-time feedback on residential energy consumption. The pilots included are heterogeneous in terms of their interventions (i.e. type of IHD and energy tariffs), geographic locations, timespans, samples, structures and designs. Additionally, not all studies have randomised treatment and control groups and the authors do not attempt to account for differences between studies in their overview.

*Impacts*: IHDs were found to cause a 3 to 13 percent decline in energy consumption, with an average 7 percent decline without prepayment of electricity and an average 14 percent decline with prepayment. However, these are rough estimates owing to the fact that some of the pilots had not concluded thereby limiting available data.

**Faruqui et al. (2014)–Connecticut** The authors review the findings from Connecticut Light & Powers "Plan-it Wise Energy Programme," a pilot involving approximately 2,200 customers conducted between June and August, 2009. The pilot programme involved residential and small commercial utility customers. Treatments included different rate structures and four enabling technologies, two of which were a real-time in-home display and the Energy Orb. Principally, the aim of the study was to better understand the effects of dynamic pricing interventions, and different enabling technologies, on residential and commercial energy usage.

*Impacts*: Customers equipped with the Energy Orb did not significant reduce their energy consumption. However, when all enabling technologies, including A/C switches and in- home displays, were combined with dynamic pricing, customers reduce their energy consumption by 23 percent.

**Fenrick et al. (2014)–Minnesota and South Dakota** The Sioux Valley Energy (SVE) pilot programme, conducted between June and August 2011, randomly selected 601 farm-rural and residential customers in Minnesota and South Dakota to test the impact of a critical peak pricing regime—including enabling technologies—on household electricity demand. The sample was divided into three groups, the first randomly selected and able to opt-out of the pilot, the second were opt-in and already had advanced metering infrastructure (AMI), and the third were randomly selected, already had AMI, and were provided in-home displays.

*Impacts*: Opt-out groups had an average peak reduction of 7 percent, while the opt-in groups peak time reduction average was 27 percent. The authors do not discuss the disaggregated effects of IHDs on peak reduction between the two opt-out groups. Additionally, the authors believe that self-selection bias is at play in the opt-in groups larger peak reduction.

**Gans et al. (2013)–Northern Ireland** Researchers examined the rollout of the Home Energy Direct Keypad in Northern Ireland using data from 18 consecutive waves of the Continuous Household Survey from 1990-91 to 2008-09. The Keypad displays real-time usage, costs, and the consumer's credit balance. Approximately 45,000 households are accounted for in the study. Those who received the Keypad metering devices were considered the treatment group, while those control group consists of all other consumers on all other plans.

*Impacts*: Between 2002 and 2009, researchers observed an 11 to 17 percent reduction in electricity consumption in households that received the smart metering devices.

**Harding and Lamarche (2016)** Households in a South Central US state were recruited to be programme participants. Participants were randomly assigned to one of three treatment groups or a control group, with roughly 200 households in each group. Treated households were assigned to a time of use pricing tariff, while control households faced a standard increasing block tariff. All treatment households received access to a web portal, which contained electricity consumption data. In addition, one group of households received an IHD, while another also received a programmable 'smart' thermostat.

*Impacts*: Receipt of an IHD (alone) did not cause households to engage in significant load shifting from peak to off-peak hours.

**Houde et al. (2013)–United States** Google "Powermeter" energy monitors randomly were provided to 752 Google employees living on the west coast, east coast, and in central United States. An additional 313 Google employees served as the control group, which was created via stratified random sampling (based on geographic region), and were only provided Powermeters 3 months after the start of the pilot. Powermeters provided participants a host of information on electricity consumption including, but not limited to, real-time usage, historical usage, projected electricity bills, time of day consumption data, and conservation tips. The study, which ran from February to October 2010, aimed to estimate the impact of real-time feedback technology on residential energy consumption.

*Impacts*: Researchers observed and average reduction in electricity consumption of 5.7 percent. However, reductions were not sustained four weeks after the intervention was introduced.

**Ivanov et al. (2013)–Andover, Minnesota** Between April 2008 and August 2010 Connexus Energy, an energy utility in suburban Andover, ran a pilot programme to test the effects of IHDs and smart meters on home energy consumption. 1,000 participants were randomly selected from within geographic

boundary of Andover. Of the 1,000, 125 households opted-in to receive IHDs and smart meters, while the other 875 households served as a control group. Data used in the study is from the months of June 2010 to the end of August, 2010. There were no rate changes during the time of the study.

*Impacts*: Households in the treatment group had an average peak rate reduction of 15 percent between June and August, 2010, when compared with the control group.

**Jessoe and Rapson (2014)–Connecticut** A sample of 437 customers (households) of Connecticut's United Illuminating Company volunteered to participate in a trial of two interventions, a time-of-use pricing regime and an in-home display, designed to reduce residential energy consumption. The trial ran from July to August 2011, and consisted of two randomly assigned treatment groups: one receiving the price intervention and the other receiving both the price intervention and enabling technology, in addition to one randomly assigned control group of 207 customers. The IHDs displayed real-time energy consumption, costs, and the consumers projected monthly bill to-date.

*Impacts*: Customers in the group that received both the price and IHD treatments saw their energy consumption decline by 8 to 22 percent. In contrast, those that only received the price intervention reduced their energy consumption by only 0 to 7 percent relative to the control group. Researchers attribute the increased energy savings of the IHD group not to price salience, but to "consumer learning."

**Lynham et al. (2016)–Hawaii** In an effort to understand the causal mechanisms at play in real- time feedbacks impact on residential energy consumption, researchers conducted a randomised control trial with 65 volunteer households in a Honolulu condominium complex. The trial was conducted in three 30 day periods, the first of which was when baseline data was collected from the households, while in the second period both treatment groups received in- home displays that provided real-time information to households in both kilowatt hours and dollars per hour. During the final period the discontinued treatment group had their IHDs removed.

*Impacts*: Researchers found that treatment groups saw an average energy reduction of 11 percent, although the cause of the reduction was attributed to consumer learning rather than price saliency. Additionally, the learning effects were found to diminish over time.

**Mukai et al. (2016)–Tokyo, Japan** Researchers in Funabashi, Japan conducted a one-month control trial from August to September 2013 to test the impact of different packaged interventions consisting of varying rate structures and feedback interventions, including a 30-minuted tiered rate, in-home displays, email notifications, and paper-based usage reports. 228 res- idents of a Funabashi condominium opted-in to the trial. All interventions were assigned randomly to three treatment groups, and the control group was created using stratified random assignment. One major drawback of the study is that all participants were exposed to the IHD and 30-minute tiered rates as part of the standard services in the condominium.

*Impacts*: Group B, which received all treatments, realised average peak savings of 11.6 percent, while there were no statistically significant reductions—when compared with the control, Group D—found for Group A, which was assigned the 30-minute tiered rate and IHDs. One caveat, noted by the researchers, is there may be underestimation effects (i.e., they have already internalised the learning effects of IHDs) in the findings because of the participants prior exposure to some of the treatments.

**Nilsson et al. (2014)–Gothenburg, Sweden** This study presents the results of two field experiments, one just outside of Gothenburg and the other inside the city, which aimed to test the impacts of in-home displays on energy consumption. The former study was held in two smaller municipalities and had a sample of 42 randomly selected households that were randomly assigned IHDs or into a control group. The second study was held in the city of Gothenburg and hand a sample of 32 households from two similar rented apartment blocks. Participants in the second study were randomly selected by the

housing manager and then randomly assigned into treatment and control groups, while further baseline data was obtained from the apartment block housing company. Both studies used the same IHD model, which displayed real-time and historical energy usage, estimated costs, and CO2 emissions resulting from participant electricity consumption.

*Impacts*: No statistically significant reductions in energy consumption relative to the control groups were found in either study. Moreover, although the study was limited by its low sample size, the researchers note that prior interest in environmental sustainability, energy savings, and knowledge of IHDs—as well as the aesthetics of the IHDs themselves—all contribute to the impact these enabling technologies have on consumer behaviour.

**Schleich et al. (2013)–Linz, Austria** Running from December 2009 to November 2010, 1,525 residential customers were randomly selected into pilot and control groups for a field trial examining the effects of real-time feedback on energy consumption. 725 participants were given the option of selecting either written or web-based feedback, while those in the control group were not notified that they were part of a feedback study. All participants were part of a larger population that had smart meters installed in their homes after their old, conventional meters had broken.

*Impacts*: Feedback group participants reduced their average energy consumption by 4.5 per- cent relative to the control group. The researchers findings also suggest that electricity consumption is inversely correlated with the frequency of billing and metering.

**Schultz et al. (2015)–San Diego, California** In a one year randomised control trial beginning in October 2012, researchers recruited 431 single family households through a postal survey and randomly assigned them to one of seven treatment groups and one control group to test the impact of social norms, different pricing regimes, and feedback. Feedback groups received ZigBee custom-coded in-home displays that used LED lights to communicate real- time usage levels below (green), at par with (yellow), or above the household average kilo- watt usage. Groups that received the norms + feedback intervention had their IHDs coded to display usage above (red), at par with (yellow), or below (green) the average of all other households, including a kWh comparison. The cost + feedback treatment group had their IHDs programme to display kWh consumption and associated costs per kWh.

*Impacts*: Only the norms + feedback group saw reductions—of 7 to 9 percent—in their energy consumption when compared with the control group.

**Sulyma et al. (2008)–British Columbia** Between November 2006 and February 2007 BC Hydro conducted a pilot programme to test the efficacy of different price signaling regimes and technologies. 2,000 residential customers, mainly single family dwellings, from the lower mainland, Vancouver Island, and northern British Columbia were randomly selected and randomly assigned into three treatment groups and a control group. Treatment groups A and B received advanced meters and different communications packages, which included periodic emails notifying them of their energy usage. Group C received the same package as B, but also had Blue Line Display Monitors (IHDs) installed.

*Impacts*: Group C experienced a 5 percent reduction in their overall energy consumption and a 9 percent reduction in peak demand—both attributable to the effect of in-home displays.

**Westskog et al. (2015)–Norway** Running from 2010 to 2014, two consecutive two-year pilot programs in Norway involving 33 participants served to investigate how in-home displays affected energy consumption in a residential setting. The 33 participants were self-recruited into the pilots and all had an annual electricity consumption falling between 20,000 and 40,000 kWh. No randomised treatment or control groups were used in either pilot; instead the sample was selected in partnership with a local housing association to approximately match the average Norwegian in terms of affluence and interest in

in energy conservation. In addition to baseline data, participants energy consumption data was compared with that of their neighbours. Participants were provided with the e-Wave in-home display during the first pilot, but technical difficulties made the data unusable. The Solo II real-time energy monitor was used in the second pilot with success.

*Impacts*: Participants in the second pilot study reduced their energy consumption by an approximate average of 12.2 percent one year after their IHDs were installed. However, due to the small sample size this is not a statistically significant finding.

**Xu et al. (2015)–Shanghai, China** Two recently built Shanghai apartment buildings received IHDs in a brief pilot programme last for the month of November, 2013. The study aimed to test how effective IHDs are in reducing home energy consumption in Shanghai. 131 respondents participated in the pilot, 76 of which received IHDs that displayed real-time energy consumption data, while 55 served as a control group. The sample was selected based on a host of socioeconomic information using a non-probability sampling technique.

*Impacts*: The treatment group reduced their energy consumption by an average of 9.1 percent over the control group. Additionally, the researchers found that introducing IHDs also led to a 12.9 percent reduction in average standby power usage when compared to the control group. One major caveat to be aware of is that there was no randomisation in the sampling and treatment assignment, in addition to little to no discussion of the methodology used.

## APPENDIX: ADDITIONAL TABLES SUPPORTING THE CASE STUDY

| | 25th percentile | Median | Mean | 75th percentile | Standard deviation |
|---|---|---|---|---|---|
| Hourly consumption (kWh) | 0.37 | 0.80 | 1.28 | 1.67 | 1.41 |
| Temperature (°C) | 0.3 | 7.8 | 7.2 | 15.8 | 10.2 |
| Price (c/kWh) | 6.6 | 7.1 | 8.4 | 10.3 | 2.3 |

**Summary statistics for the case study data set.** The sample consists of 6,881 households observed hourly over a 2-year period from September 2012 to September 2014. There are a total of 117 million hourly observations of household electricity consumption. The electricity price is deflated by the Ontario consumer price index, and temperature is measured at a nearby monitoring station maintained by Environment Canada.

| | (1) | (2) |
|---|---|---|
| IHD | -0.031*** (0.007) | -0.032*** (0.008) |
| Date-hour FE | Yes | Yes |
| Household-hour FE | Yes | Yes |
| Sample | All days | Weekends |
| $R^2$ | 0.440 | 0.440 |
| Observations | 115,413,459 | 33,097,750 |

**Main regression results**. The table shows the results of a regression of hourly electricity consumption on a dummy variable indicating whether a household has been sent an IHD as well as fixed effects as described in the text and in Martin and Rivers (2015). Column (1) uses all observations while column (2) restricts the sample to weekends.

| | (1) | (2) |
|---|---|---|
| log(price) | -0.377*** (0.141) | -0.167*** (0.068) |
| IHD x log(price) | 0.173*** (0.057) | -0.074 (0.052) |
| Date FE | Yes | Yes |
| Household-hour FE | Yes | Yes |
| Temperature bins | Yes | Yes |
| Covariates | Yes | Yes |
| Sample | Winter weekdays | Summer weekdays |
| $R^2$ | 0.542 | 0.519 |
| Observations | 5,865,587 | 6,672,141 |

**Regression results to determine the effect of IHD on price responsiveness.** This table show the results of a regression that restricts the sample to weekdays within 30 days of a change in the electricity pricing tariff, as illustrated in Figure 6. Each column in the table is based on a balanced panel of households within the window, who do not alter their IHD status over the duration of the 60-day window. Regressions include dummy variables to indicate outdoor temperature, as well as covariates to capture changes in daylight and time trends interacted with hour dummy variables. Column (1) presents results for the change in electricity tariff in winter 2013, and column (2) presents the results for the change in electricity tariff in summer 2013.