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On the Effectiveness of Smart Metering Technology Adoption: Evidence from the National Rollout in the United Kingdom

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Abstract

In response to the burgeoning threats of climate change to humanity, numerous governments, such as those of the United States and most European countries, have launched rollout programs for the distribution of smart metering technology (SMT). Despite this notable recent investment, questions of whether and why SMT adoption facilitates the reduction of households' energy demands remain relatively unexplored. Building on cognitive dissonance theory, we propose a research model for SMT adoption, residential energy-saving behaviors, and moderating factors. We then empirically test the model using a rich household dataset from the United Kingdom between 2012 and 2016. Our results show that SMT adoption is positively associated with energy-saving behaviors, while energy-saving motivations substantially moderate this association—a lower level of concern about saving energy / a higher level of concern about climate change amplifies this effect. Importantly, we find that SMT usage positively moderates this relationship, but this marginal gain decreases in technology usage intensity. Our findings contribute to the information systems literature by showing a consequence of new technology adoption along with the role of cognitive dissonance in promoting intended objectives and identifying potential moderating effects. We discuss actionable insights for policymakers and utility firms.

Keywords: Smart Meter Technology, Household Technology Adoption, Energy-Saving Behavior, Cognitive Dissonance Theory

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1 Introduction

The rapid rate of climate change is introducing severe threats to humanity—for example, new and more frequent disease outbreaks and the potential for large numbers of climate refugees due to extreme weather events and rising sea levels (Cann et al., 2013; Coumou & Rahmstorf, 2012). In order to slow down or stop climate change, a substantial reduction in greenhouse gas emissions is necessary (Elliot, 2011; Melville, 2010). As the transition to renewable energy on the supply side alone is not sufficient to tackle this challenge (Piel et al., 2017), numerous governments, including those of the United States (US) and most European countries, have launched initiatives to build information systems-enabled power grid infrastructures, based on the communication of energy information between suppliers and consumers through smart metering technology (SMT). The Obama administration announced the expanded deployment of SMT as a primary vehicle for empowering customers to save energy and assigned a 1 billion USD budget to this purpose (The White House, 2009). The European Union (EU) declared that the vast majority of traditional electricity metering devices would be replaced with SMT despite high installation costs ranging between EUR 200 and 250 per household (European Commission, 2018a).

Such substantial investment in the rollout is based on the assumption that SMT adoption and usage will result in positive outcomes. Previous studies on technology adoption have supported this assumption by investigating whether adoption, in itself, can be considered a success from an organizational or governmental perspective (Venkatesh et al., 2003; Venkatesh et al., 2012; Srivastava et al., 2016). However, these studies have largely overlooked the household perspective, particularly in terms of sustainable technology (Venkatesh & Brown, 2001; Venkatesh et al., 2012; Wunderlich et al., 2019). Unlike other sustainable technologies, such as solar panels and electronic vehicles, SMT per se does not directly provide alternative energy sources or replace the use of fossil fuels. Instead, it can influence environmental outcomes only by informing users about their energy usage and subsequently expecting altered energy-consumption behaviors (Jessoe & Rapson, 2014). Therefore, SMT adoption does not necessarily translate into a reduction in energy consumption.

Nevertheless, similar to the research stream on technology adoption, existing studies typically concentrate on the antecedents as opposed to the consequences of sustainable information technology (IT) adoption (Blut et al., 2022; Gholami et al., 2013; Marett et al., 2013; Venkatesh et al., 2016; Warkentin et al., 2017). Regarding household technology, the research is still nascent (Wunderlich et al., 2019). Although a few studies have examined the consequences of households' sustainable IT adoption and developed theoretical models (e.g., Carroll et al., 2014), to the best of our knowledge, there has been limited effort to explain the heterogeneous effects of sustainable IT adoption on behavioral changes depending on resource-saving motivations and usage patterns.

Given this research gap, we propose a research model of sustainable IT adoption and subsequent behavioral changes and empirically validate it within the SMT adoption context. Building on the theory of cognitive dissonance, we propose that SMT adoption will contribute to facilitating energy-saving behaviors by disconfirming households' prior beliefs about their own consumption and inducing cognitive dissonance. Put simply, the more that households' actual use exceeds their own perceptions of energy use, the higher the cognitive dissonance and thus the higher energy-saving behaviors. Also, these effects are moderated by energy-saving motivations and technology usage intensity, which are associated with the level of dissonance. To validate our proposed model, we collected a rich dataset of nationally representative households during the real-world rollout policy in the UK between 2012 and 2016.

Our empirical findings mostly support these hypotheses. SMT adoption is associated with a significant increase in energy-saving behaviors but the relationship is moderated by energy-saving motivations. When residential consumers are highly concerned about saving energy, they are less likely to reduce energy demands. Conversely, the reduction in energy demands is amplified as consumers are more concerned about climate change. Technology usage intensity—i.e., frequency of monitoring in-home displays (IHDs)—is positively associated with energy-saving behaviors, and households that monitor IHDs less frequently demonstrate no significant difference from those monitoring IHDs every day. Robustness checks suggest that our findings are unlikely to be spurious.

Our work contributes to research by providing a model for understanding the effects of SMT adoption on energy-saving behaviors and providing field evidence from the UK SMT rollout policy. Given that substantial heterogeneity exists across energy-saving motivations, researchers should consider the expected outcomes of adopting sustainable technology as well as the adoption itself to achieve optimal environmental and operational performance. Importantly, we provide empirical evidence that using sustainable IT increases environmental outcomes but that the marginal increase in the outcomes decreases with usage intensity. This implies that technology usage after adoption is necessary for altering target behaviors but improving usage intensity may not further boost target behaviors. These findings provide several valuable directions for future research.

Our paper also provides a number of implications for utility firms and policymakers. For instance, our findings imply that the higher penetration rates of smart meters do not ensure the effectiveness of smart energy systems. We find significant heterogeneity of SMT-induced saving across energy-saving motivations, which is possibly associated with prior knowledge of households' own consumption. Thus, utility firms should carefully consider which households to target based on the expected benefit to achieve higher reductions in energy demands. Further, if heterogeneous effects are unexpected to adopters, such gaps might induce disconfirmation of technology performance expectations, which could result in negative experiences and emotions (Marikyan et al., 2020). Therefore, our insights on heterogeneity and the underlying mechanisms might help improve user experiences, which could in turn elicit more positive attitudes toward resource and environmental policies.

2 Background

2.1 Smart Grids and the Rollout Program for Smart Meter Technology

The smart grid has been introduced to improve capabilities and address growing energy demands and carbon emissions. It is defined as a modern power grid infrastructure that uses automated controls and state-of-the-art communication technologies to achieve enhanced efficiency, reliability, and safety (Gungor et al., 2011). Smart grids require online communication between smart meters and utilities' back-haul systems in the form of a two-way communications network. Such a network enables various demand-side management strategies involving distributed energy generation and storage to meet energy demands. Smart grid programs have been initiated to help energy consumers maintain expenses at an affordable level, given unpredictable global energy prices (The US Department of Energy, 2008; Sovacool, 2013). In particular, smart meter programs have received much attention from governments and businesses, as SMT is a fundamental component of the smart grid, connecting and informing energy consumers. For example, in 2009, the US government announced an investment of US$ 3.4 billion to spur the transition to a smart energy grid (The White House, 2009). The EU aims to replace 80% of traditional electricity meters with smart meters by 2020 (European Commission, 2018a). The rollout of smart grids and SMT are expected to abate carbon emissions by up to 9%; therefore, most EU countries are now participating in their own SMT rollout programs despite high estimated costs ranging from EUR 200 to 250 per customer (European Commission, 2018b).

Our empirical context focuses on the UK government's SMT rollout program. The UK proclaimed a goal for all households and small businesses to have smart meters by 2020 and mandated that energy suppliers are responsible for their installation (Ofgem, 2015). The UK's "Smart Meter Implementation Programme" consisted of three stages: (1) the policy design stage, (2) the foundation stage, and (3) the main installation stage. In the first stage, numerous initial decisions were made between July 2010 and March 2011, and the Office of Gas and Electricity Markets (Ofgem) managed the project on behalf of the Department of Energy and Climate Change (DECC). In the second stage, government departments, the energy industry, consumer groups, and other stakeholders worked together to complete the groundwork before energy suppliers began the process of providing smart meter devices to most of their customers. During this period, the government's goal was to allow the industry to develop systems, discover what consumers' preferences were, and learn how to help consumers effectively utilize smart meters. In the last stage, which commenced in 2016, most customers were supposed to have smart meters installed. During the rollout, consumers were able to have smart meters installed at no extra cost upon request, though they were not obliged to do so.

Despite governmental support, the actual adoption rate is still far behind the government's goal. In 2016, at the end of our research period, the adoption rate had barely reached 20%. In 2018, still only 31% of households had adopted SMT (DECC, 2018), leading the UK government to recently push back the deadline by four years to 2024 (Ambrose, 2019). The National Audit Office indicated that implementation costs are rising with the delay of the rollout, and consumers face paying GBP 500 million more than initially estimated, even when potential marketing costs are not included (Vaughan, 2018). Field experts and researchers pointed out that the deferred implementation could be partially attributable to high installation costs and low perceived values (Macalister, 2014; Sankar et al., 2013; Vaughan, 2018). For these reasons, as long as energy suppliers and policymakers pursue energy savings and reliability of energy grids (European Commission, 2018b; The White House, 2009), they need to understand when and how SMT adoption contributes to a demand reduction in order to optimally allocate limited resources.

2.2 Related Literature

The research stream on household technology adoption has focused mainly on the antecedents of behavioral intention (Brown & Venkatesh, 2005; Venkatesh & Brown, 2001; Venkatesh et al., 2016). Similarly, in the literature on the adoption of sustainable technologies, which aims to incorporate environmental, social, and financial considerations (Charter & Clark, 2007), numerous studies have investigated determinants of adopting sustainable technologies, such as electric cars, photovoltaic systems, and local renewable energy systems (Korcaj et al., 2015; Lee et al., 2016; Noppers et al., 2014).

SMT has also been examined through the lens of sustainable innovation, as it is considered a vehicle for reducing carbon emissions and energy consumption. For example, Kranz and Picot (2012) showed that environmental concern has a positive effect on adoption intention, separate from the attitude toward technology. Similarly, Gerpott and Paukert (2013) suggested that residential customers' environmental awareness is positively associated with willingness to pay for smart meters. Conversely, Noppers et al. (2016) found that perceived environmental attributes of smart meters were not associated with participation in the smart metering project. Prior studies also focused on IT-specific aspects of SMT. For instance, they raised questions about privacy concerns that stem from the possibility that information collected and harnessed to provide services might be used for other purposes or provided to unauthorized third parties (Chen et al., 2017; Warkentin et al., 2017). Wunderlich et al. (2019) showed that a residential consumer's perceived privacy risk (inherent innovativeness) is negatively (positively) associated with the intention to adopt SMT.

Closer to our research questions, scholars have examined the impact of sustainable technology adoption on resource consumption. Degirmenci and Recker (2018) showed that an email reporting system for reflective disclosure and an online discussion forum led to a significant reduction in paper printing. Prior studies on energy web portals have also shown that displaying environmental information (e.g., carbon emission amounts) outperforms showing monetary information in terms of energy demand reduction (Asensio & Delmas, 2015; Spence et al., 2014). With respect to household technology, Loock et al. (2013) examined how an online feedback service provided by a utility company stimulated energy-efficient behaviors in private households. They found that goal-setting features in the online service facilitated energy savings and that feedback helped correct energy consumption behaviors to achieve goals. Tiefenbeck et al. (2018) showed that real-time feedback from digital devices significantly reduced water usage, and Tiefenbeck et al. (2019) revealed that this effect remained significant even in the absence of program participation self-selection and monetary incentives.

In the context of SMT adoption's effect on residential energy consumption, Faruqui et al. (2010) reviewed previous studies on smart meters and suggested that the basic feedback provided by in-home displays (IHDs) reduced demand by 3-10%. Carroll et al. (2014) empirically showed that feedback from smart meters led to simultaneous improvements in both consumers' information about their own resource consumption and demand reduction. Houde et al. (2013) revealed that real-time feedback led to a more considerable reduction in electricity use during morning and evening intervals. Schleich et al. (2017) found that the effects of feedback persisted over an 11-month period.

Despite these efforts, a formal framework to understand the underlying mechanisms for the effectiveness of SMT adoption has not been suggested in previous studies. Our research intends to contribute to the literature by proposing a framework of cognitive dissonance mechanisms for the heterogeneous effects of SMT adoption on energy-saving behaviors, considering contingent factors in terms of saving motivations and technology usage intensity, and empirically validating the proposed relationships. Importantly, to the best of our knowledge, the relationship between the usage intensity of SMT (i.e., monitoring frequency) and energy-saving behaviors has been neither proposed nor empirically examined in the extant literature. We summarize the literature on the impact of sustainable technology adoption on resource consumption behaviors, along with our contributions, in Table 1.

3 Research Model and Hypotheses

3.1 Cognitive Dissonance Theory

Festinger's (1962) cognitive dissonance theory (CDT) proposes that when people hold psychologically inconsistent cognitions, they will experience cognitive dissonance. The dissonance makes people uncomfortable and they thus seek to re-establish consistency. Thus, when people face such inconsistencies, they may undertake measures to reduce cognitive discrepancies, such as attitude change, consonant information-seeking, and behavior change (Festinger, 1962; Marikyan et al., 2020).

With respect to our research context, SMT adoption can inform users about their own energy consumption (Noppers et al., 2016). Cognitive dissonance may arise when the expected level of one's own consumption is inconsistent with the information delivered through an in-home display (IHD). There might be several types of responses to this dissonance.

1. Individuals may alter their attitude toward energy-saving such that their current consumption level can be justified. If so, such individuals will not change their behaviors.
2. Individuals may seek consonant information to support their prior beliefs. Specifically, they may suspect the performance of SMT and compare the expected information shown on the IHD with their actual energy bills. Even if they undertake such a measure, the dissonance may not be resolved as long as SMT provides accurate information.
3. Individuals may change their consumption level until it meets their expectations. If SMT adopters behave in such a manner, we will observe significant behavior changes.

We propose that the cognitive dissonance evoked by SMT adoption will be consistent with the third possibility rather than the first or second possibilities, and that users will adjust consumption to meet their expectations. First, prior studies have shown that residential consumers are willing to change their resource consumption behaviors when they are informed more saliently about actual consumption (Sexton, 2015; Tiefenbeck et al., 2018). This suggests that consumers have sufficient control over their behaviors, indicating that they do not have to alter their existing thoughts to reduce cognitive dissonance. Second, studies have suggested that SMT adoption facilitates consumers' knowledge of their own energy usage (Carroll et al., 2014; Jessoe & Rapson, 2014), suggesting that consumers do not doubt the information provided through IHDs, at least in the long term.

Table 1. Previous Research on the Impact of Sustainable Technology Adoption on Resource Consumption

Authors	Sample	Context	Main findings	Heterogeneous effects		
				Findings	**Theoretical framework**	**Technology usage intensity**
Houde et al. (2013)	An opt-in sample of 1,065 households in the US (2010)	Web-based real-time feedback for electricity consumption	Access to feedback reduces household electricity consumption, and the effect persists for up to four weeks.	No household characteristics explained variation in treatment effects.	No	Not considered
Loock et al. (2013)	1,791 Austrian residential consumers registered on a website	The web-based feedback system for electricity consumption	A goal-setting functionality in a web portal substantially improves energy conservation, and default goals moderate their effectiveness.	No	No	Not considered
Carroll et al. (2014)	2,722 nationally representative Irish households (2009-2010)	Real-time feedback on energy consumption via smart meters	Increased feedback leads to a reduction in electricity demand and improvements in the stock of energy-reducing information.	Households using high-energy-consuming appliances show larger reductions.	No	Not considered (improvements in information were considered only)
Spence et al. (2014)	153 for Study 1 (102 for Study 2) undergraduate students recruited by email (online messages) in a UK university	A web tool that calculates participants' energy usage and provides feedback	Carbon dioxide information is more persuasive than kilowatt-hours and monetary information because CO_2 information increased climate change salience.	No	No	Not considered
Asensio and Delmas (2015)	118 households registered on a website in LA	The web-based feedback system for electricity consumption	Environment and health-based information outperform monetary savings information in energy savings.	Previous electricity usage (+), having children (+)	No	Not considered
Tiefenbeck et al. (2018)	An opt-in sample of 636 one- and two-person households in Switzerland	Real-time feedback on water consumption while showering via digital devices	Real-time feedback induced substantial resource conservation.	Previous water usage (+), environmental attitude (+)	No	Not applicable (technology usage frequency is virtually equal to showering frequency)
Schleich et al. (2017)	1,525 Austrian households who adopted smart meters	Real-time feedback on energy consumption via smart meters	Feedback reduces electricity consumption over an 11-month period.	No	No	Not considered
Degirmenci and Recker (2018)	95 employees in a large Australian university	An email reporting system and an online discussion forum about paper printing	Reflective disclosure and information democratization reduce paper printing.	No	No	Not considered

Tiefenbeck et al. (2019)	Guests (265 rooms, 19,596 observations) at six Swiss hotels	Real-time feedback on water consumption while showering via digital devices	Real-time feedback substantially reduced resource consumption in the absence of volunteer selection bias and financial incentives.	No	No	Not applicable (technology usage frequency is virtually equal to showering frequency)
This study	8,125 nationally representative households in the UK (2012-2016)	Real-time feedback on energy consumption via smart meters	Smart meter adoption significantly facilitates energy-saving behaviors for nationally representative residents.	Concern about saving energy (–), concern about the environment (+), decreasing returns to monitoring efforts	Cognitive dissonance theory	Energy-saving behaviors increase with technology usage intensity but at a decreasing rate.

Lastly, the extant literature on energy and resource consumption suggests that interventions evoking cognitive dissonance induce resource savings, rather than altering attitudes or making them suspicious of information. For instance, Kantola et al. (1984) showed that becoming informed about the inconsistency between attitudes toward conservation and actual electricity usage leads to a significant reduction in the demand for electricity. Dickerson et al. (1992) demonstrated that artificially aroused dissonance that makes people feel hypocritical about their showering habits leads them to save more water. For these reasons, we propose that behavioral changes and cognitive dissonance will have the following relationship:

$$\text{Behavioral changes} \propto \text{Cognitive dissonance} \equiv \text{Informed level - Expected level.}$$

This indicates that behavioral changes are positively associated with the level of cognitive dissonance, which is equivalent to the difference between expected and actual consumption levels. Note that SMT provides real-time feedback on energy use intensity, helping consumers to effectively evaluate various energy-saving efforts. Hence, SMT adopters can find and maintain their optimal saving behaviors over the long term.

It is worth mentioning that consumers may perceive their consumption amount to be either larger or smaller than the actual amount. Therefore, feedback might imply underconsumption as well as overconsumption. Despite this potential heterogeneity, the extant literature has suggested that less accessibility or salience of information leads to the overconsumption of resources, on average (Sexton, 2015; Tiefenbeck et al., 2018). Therefore, we predict that SMT adoption will significantly boost energy-saving behaviors for average consumers.

H1: Households' adoption of SMT will be positively associated with energy-saving behaviors.

3.2 Energy-Saving Motivations and Biased Expectation in Own Consumption

Our first hypothesis suggests that the effect of SMT adoption on energy-saving behaviors will be determined by the extent to which consumption feedback evokes cognitive dissonance between a household's expected and actual consumption levels. We expect that a bias in expectations will moderate this relationship. Specifically, a larger bias implies that a more significant loss from suboptimal consumption has occurred. Thus, consumers will be more motivated to correct their behaviors.

In this regard, we predict that energy-saving motivations will significantly affect the expectation bias. Residential consumers who are more concerned about saving energy may have different responses to information feedback compared to general consumers. These consumers are likely to have already made more efforts to save energy, checked their bills, and been more informed about energy usage and costs before SMT installation (Gerarden et al., 2017; Sallee, 2014; Sexton, 2015). Even if such consumers had higher expected reductions than actual energy reductions, this gap would have already been resolved before adopting SMT due to frequent bill-checking behaviors. Therefore, consumption information delivered through SMT may not be substantially different from prior beliefs concerning their own consumption amounts. If feedback on energy consumption does not deliver new information, SMT adoption will not update the prior knowledge of these consumers. This will motivate consumers to maintain their current saving behaviors and not exert additional effort. As a result, SMT adoption will arouse less dissonance for such consumers. We hypothesize that:

H2: Households that are more concerned about saving energy will exhibit a less significant relationship between SMT adoption and energy-saving behaviors than households that are less concerned about saving energy.

Prior studies have suggested the possibility that altruistic motivations can also explain energy-saving behaviors (Dietz, 2015; Warkentin et al., 2017). In addition to the direct benefit from reduced energy bills, energy conservation leads to two potential positive externalities. First, collective energy savings allow utilities to avoid the need for expensive peak-demand power generation (Warkentin et al., 2017). Reductions in peak demand can significantly decrease the risks of brownouts and blackouts, eventually enhancing national energy security. In this regard, we expect that residential consumers who are more concerned about national energy security will perceive more benefits from energy-saving behaviors than those who are less concerned. In line with our argument, the extant literature has revealed that perceived energy security and environmental risks increase the overall evaluation of electric vehicles and associated policies (Bockarjova & Steg, 2014).

Second, an overall reduction in energy consumption decreases carbon emissions, thus slowing the progress of climate change (Hledik, 2009; Loock et al., 2013). In this vein, we expect that consumers who are more concerned about climate change will extract higher value from saving energy. Several studies have also suggested that one's environmental concerns and attitudes are positively associated with pro-environmental behaviors (Gadenne et al., 2011; Kaiser et al., 1999; Martinsson et al., 2011; Sapci & Considine, 2014).

We propose that without SMT adoption, consumers having such altruistic motivations are more likely to expect that they sufficiently conserve residential energy, regardless of how frequently they check their billing information. Based on our suggested relationship, cognitive dissonance can occur for such consumers when their expected level is sufficiently low. In other words, without SMT adoption, it is more likely that their actual consumption levels are higher than their expected levels (Sallee, 2014; Sexton, 2015). If there is indeed a significant discrepancy between their actual consumption levels and their expected levels, this could induce altruistically motivated consumers to feel hypocritical about their energy use behaviors (Dickerson et al., 1992). Thus, they will likely make a greater effort to reduce their energy use than average consumers. We therefore hypothesize that:

H3: Households that are more concerned about national energy will exhibit a more positive relationship between SMT adoption and energy-saving behaviors than households less concerned about national energy.

H4: Households that are more concerned about climate change will exhibit a more positive relationship between SMT adoption and energy-saving behaviors than households less concerned about climate change.

3.3 Decreasing Returns to Technology Usage

Many studies have stressed the importance of post-adoption outcomes, such as continuous usage of technology (Blut et al., 2022; Venkatesh et al., 2003; Venkatesh et al., 2012; Marett et al., 2013; Kang et al., 2020). In particular, the extant literature has emphasized that the assumption that successful technology adoption and continuous usage will lead to success in organizational or governmental outcomes needs to be empirically validated (Venkatesh et al., 2003; Venkatesh et al., 2016; Srivastava et al., 2016). However, studies on household technology adoption have also postulated that adoption per se relates to target behaviors and often neglected the role of continuous usage (e.g., Wunderlich et al., 2019). In particular, most sustainable IT adoption studies have postulated that adopting a technology would lead to monitoring behaviors and energy savings via information feedback; however, they have not examined how usage or monitoring intensity moderates the path to resource-saving behaviors (Faruqui et al., 2010; Houde et al., 2013; Loock et al., 2013; Carroll et al., 2014; Schleich et al., 2017).

Although the relationship between technology usage intensity (or frequency) and target outcomes has received little attention in our context, there are some related studies on monitoring and weight loss in the healthcare literature. Burke et al. (2012) found that providing self-monitoring devices with daily feedback for weight loss outperforms self-monitoring with paper diaries. Turk et al. (2013) showed that providing more frequent feedback can assist in weight loss by facilitating self-monitoring adherence. Similarly, Peterson et al. (2014) showed that frequent self-monitoring is significantly associated with weight loss only when individuals consistently check their weight over time. These studies suggest that feedback and monitoring efforts do help with weight loss but that more frequent access to information does not improve outcomes. Instead, self-oriented and regular access to information is more helpful for obtaining meaningful information. This might suggest that monitoring with a moderate interval may provide meaningful information about individuals' weight or diet trends. However, variations in weight or dietary information within a short period can be too noisy to be applied to behavioral changes. For instance, body weight substantially varies within a day, so monitoring multiple times in a day is not informative for understanding one's health status (Vivanti et al., 2013). Hence, individuals may be unable to clearly understand the necessity of changing their behaviors.

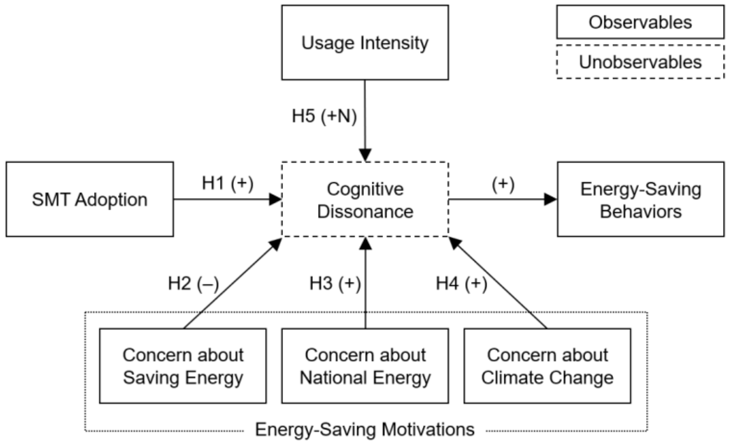


Figure 1. Research Model

Likewise, an increase in energy-conserving behaviors may show decreasing returns to SMT usage or IHD monitoring intensity. According to the extant literature, energy-consumption patterns are highly noisy and periodic within a day and even within a week (Kwac et al., 2014; Eom et al., 2020). Therefore, although the appropriate interval might differ from the weight loss context, relatively sparse but regular monitoring can inform households about notable differences in cumulative energy usage and expected bills, which will enable them to compare their beliefs with their actual consumption. Conversely, monitoring IHDs frequently within a short period will not necessarily provide meaningful information. Therefore, households may not gain additional information that can disconfirm their beliefs about their own energy consumption through excessive efforts to monitor their own consumption using IHDs. For these reasons, we hypothesize that:

H5: SMT usage intensity will be (a) positively associated with energy-saving behaviors, and (b) with a decreasing rate of intensity.

Figure 1 depicts the research model that summarizes our hypothesized relationships.

4 Data Description

4.1 Data Source

We obtained household data from a yearly survey administered to households in the UK by the Department of Energy and Climate Change (DECC). The DECC administers this survey to understand and monitor public attitudes toward its main business priorities, which include national energy supplies and actions to mitigate climate change. This survey is performed at the national level through face-to-face in-home interviews with a representative sample of UK households. Specifically, the sample is drawn from a small set of homogeneous streets for each interviewer through a random location quota sampling method based on sex, age, social grade, region, and housing tenure. Hence, interviewers are given little choice in their selection of respondents. The survey has been administered in late March every year since 2012; about two thousand households are surveyed each year but households cannot be tracked over time (DECC, 2014).[1]

In 2012, 47.8% of UK households were aware of smart meters but the penetration rate of smart meters only reached 6.0%. After four years, 74.0% of households answered that they had heard of smart meters and 19.9% reported that they had installed them. Notably, penetration rates rapidly increased between 2012 and 2014, but the rate of increase has slowed down since 2014. During the research period, we did not find external shocks that would have striking effects on households' decisions concerning smart meters (DECC, 2017; Ofgem, 2015).[2]

[1] We used the Public Attributes Tracker dataset, comprising a main annual survey every March and three shorter surveys in other seasons. Since our main interest (adoption of smart meters) was measured only in the main survey, we excluded the shorter surveys from our analysis.

[2] First, governmental policies on smart meters were highly stable during the period. The UK government's rollout program consists of three stages. Our research period begins in March 2012 and ends in March 2016 and mostly comprises the second stage only (the foundation stage); thus, we do not expect major policy changes. Second, we checked the possibility that dramatic changes in global fossil fuel prices—from \$112 per barrel in 2012 to \$48 in 2016—may have affected our results. The fuel price index numbers relative to the GDP deflator of the UK suggest that gas prices did not decrease significantly (from 118.3 to 113.1), and electricity prices increased slightly between 2012 and 2016 (from 109.4 to 116.4). Thus, we believe that changes in fossil fuel prices were not so influential that they eclipsed the impacts of other factors.

4.2 Measurements

Table 2 shows how household characteristics and behavioral outcomes are defined and provides their descriptive statistics. Our data consists of the adoption of SMT, usage intensity, energy-saving behaviors, energy-saving motivations, and household characteristics that are either explicitly coded or inferred using exploratory factor analysis. For each survey item, we screened out households that answered "Don't know" or "Not applicable," except for household income, to which nearly 30% of respondents did not give answers. We thus obtained 8,125 household-level observations over five years.

4.2.1 SMT Adoption, Usage Intensity, and Energy-Saving Behaviors

SMT adoption: In the DECC survey, pictures and descriptions of smart meters are provided, and the respondent is asked the following question: "Before today, had you heard of smart meters? [If yes, ask] Do you have one?" A respondent might select either "Yes, I have one," "Yes, but I do not have one," or "No—I have never heard of them." Respondents who selected "Yes, I have one" are classified as *adopters*. Throughout the research period, 14% of respondents had installed SMT in their homes.

Usage intensity: Given that SMT provides energy-consumption and expected billing information through in-home displays (IHDs), the usage intensity of SMT can be defined as how frequently a household monitors their IHD. In this survey, an IHD is defined as "a portable device that displays current and past energy usage and how much it is costing or will cost." Since some SMT adopters were offered alternative monitoring options—e.g., online or television channels—instead of IHDs, we excluded these households in analyzing usage intensity.

Among households that installed IHDs, usage intensity was divided into three levels: (1) those who never look at it, (2) those who look at it occasionally, and (3) those who look at it every day. For ease of interpretation, we defined *monitoring at least occasionally* as 1 if a household looked at the display either occasionally or every day, and 0 otherwise, and *monitoring every day* as 1 if a household looked at the display every day, and 0 otherwise. Households that monitored IHDs every day belong to a subset of households that looked at the display at least occasionally.

Energy-saving behaviors: SMT does not provide additional energy supplies or directly affect energy efficiency. Hence, SMT affects energy demands via changing consumers' behaviors only. In this study, energy-saving behaviors were measured by five items, such as "Leave the lights on when you are not in the room" (a wasting behavior, negative) and "Try to keep rooms that you are not using at a cooler temperature than those you are using" (a saving behavior, positive). Each item was originally rated on a 5-point Likert scale from 1 = *Never* to 5 = *Always*. However, to incorporate items into a single variable, we scored wasting behaviors from 1 = *Always* to 5 = *Never*. We averaged the scores for the five items to operationalize this construct. Since each activity contributes to energy conservation independently and they are not interchangeable, we regard energy-saving behavior as a formative construct (Petter et al., 2007).

4.2.2 Energy-Saving Motivations

Concern about saving energy: We defined this covariate as the extent to which a household pays attention to saving energy in the home. It was measured by a single 4-point Likert-type scale item, "How much thought, if any, would you say you give to saving energy in your home?" from 1 = *None at all* to 4 = *A lot*. As the level of thought reflects how important an individual considers an issue to be, we postulated this measure as a proxy for concern about saving energy.

Concern about national energy (CNE): We defined concern about national energy as the extent to which a household worries about energy independence and the stability of the UK. It was measured by four items such as: "The UK becoming too dependent on energy from other countries" rated on a 4-point scale from 1 = *Not at all concerned* to 4 = *Very concerned*. This construct reflects households' worries about general energy supplies to the public; hence, we postulated that CNE in part reflects individuals' valuation of the shared benefit of avoiding disruptions in collective energy supplies (Warkentin et al., 2017).

Concern about climate change (CCC): In this research, concern about climate change is measured by a single 4-point scale item: "How concerned, if at all, are you about climate change, sometimes referred to as 'global warming'?" Attitudes and concerns about climate change are closely associated with general environmental beliefs (O'Connor et al., 1999). Similarly, Poortinga et al. (2004) regarded concern about global warming as one of the major environmental concerns. Furthermore, this measurement is highly similar to the operationalization of environmental attributes of SMT by Noppers et al. (2016), who used carbon emission and global warming as two of three items for the construct.

4.2.3 Control Variables

To control for potential confounding factors, we included additional constructs extracted from the exploratory factor analysis, such as concern about daily expenses and attitude toward renewable energy. In addition, we controlled for several household characteristics, including age, gender, region, household size, presence of children, income amount, social class (categorical), and housing tenure (categorical). We report the description (summary statistics and correlations) of the variables in Table 2 (Table 3). We describe further details in Appendix A.

Table 2. Variable Descriptions

Variables	Description	Obs.
SMT adoption	1 if a household adopted SMT; 0 otherwise	8,125
Monitoring at least occasionally^{+}	1 if a household looked at the display either occasionally or every day; 0 otherwise	7,644^{+}
Monitoring every day^{+}	1 if a household looked at the display every day; 0 otherwise	7,644^{+}
Energy-saving behaviors	The sum of the frequency of independent energy-saving behaviors	8,125
Concern about saving energy	The extent to which a household pays attention to saving energy in the home	8,125
Concern about climate change	The level of concern about climate change or global warming	8,125
Concern about national energy	The extent to which a household worries about energy independence and the stability of the UK	8,125
Concern about daily expenses	The level of concern about household expenditure	8,125
Attitude toward renewable energy	The extent to which a household supports the use of renewable energy	8,125
Age	A respondent's age (ordinal)	8,125
Female	1 if a respondent is female; 0 otherwise	8,125
Rural	1 if a household is in a rural area; 0 otherwise	8,125
Household size	The number of people living in a household	8,125
Having a child	1 if there is a child in a household; 0 otherwise	8,125
Income reported	1 if a respondent reported his/her household income; 0 otherwise	8,125
Income reported × Amount	A household's yearly income (ordinal) if a respondent reported his/her household income, 0 otherwise	8,125
Social class	Classification of households based on a chief income earner's occupation (categorical)	8,125
Housing tenure	The financial arrangements under which the household has the right to live in a house or apartment (categorical)	8,125

Note: $^{+}$When using these variables, we excluded SMT adopters who did not adopt in-home displays (IHDs), given that they adopted alternative channels such as online webpages and television.

Table 3. Summary Statistics and Correlation Matrix for Continuous Variables

Variables		Mean	Range	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.
1	SMT adoption	0.141	[0, 1]	.														
2	Monitoring at least occasionally	0.066	[0, 1]	0.63**	.													
3	Monitoring every day	0.023	[0, 1]	0.36**	0.58**	.												
4	Energy-saving behaviors^	3.631	[1, 5]	0.06**	0.06**	0.04**	.											
5	Concern about saving energy ^	3.026	[1, 4]	0.05**	0.05**	0.06**	0.30**	.										
6	Concern about climate change^	2.941	[1, 4]	0.00	0.00	0.00	0.15**	0.18**	.									
7	Concern about national energy^	2.810	[1, 4]	-0.01	-0.01	0.00	0.14**	0.19**	0.37**	.								
8	Concern about daily expenses^	2.124	[1, 4]	0.00	-0.02*	-0.02	0.03**	0.09**	0.12**	0.20**	.							
9	Attitude toward renewable energy^	3.989	[1, 5]	0.00	0.00	0.01	0.14**	0.13**	0.27**	0.26**	0.05**	.						
10	Age	3.587	[1, 6]	-0.09**	-0.03**	-0.02	0.07**	0.14**	-0.04**	0.05**	-0.19**	-0.14**	.					
11	Female	0.515	[0, 1]	-0.02*	-0.02	-0.01	0.03**	0.03**	0.05**	-0.02	0.04**	-0.06**	-0.03*	.				
12	Rural	0.200	[0, 1]	-0.02*	-0.02	0.00	0.00	0.01	0.01	0.04**	-0.03**	0.02	0.08**	0.01	.			
13	Household size	2.653	[1, 5]	0.08**	0.04**	0.06**	-0.07**	-0.03**	0.05**	0.02	0.14**	0.08**	-0.45**	0.03*	-0.03**	.		
14	Having a child	0.302	[0, 1]	0.10**	0.05**	0.05**	-0.05**	-0.02	0.03**	0.00	0.16**	0.05**	-0.38**	0.11**	-0.01	0.63**	.	
15	Income reported	0.717	[0, 1]	0.06**	0.02*	0.01	-0.01	0.00	0.03*	0.02*	0.02	0.04**	-0.02	-0.01	0.00	0.00	0.06**	.
16	Income reported × Amount	1.843	[0, 5]	0.02	0.02*	0.01	-0.05**	-0.01	0.08**	0.07**	-0.10**	0.12**	-0.09**	-0.05**	0.01	0.17**	0.11**	0.66**

Note: ^The selected variables are normalized in the analysis for ease of interpretation. Summary statistics are weighted by the inverse of the likelihood with which each individual is sampled. *$p < 0.5$; **$p < 0.01$.

5 Empirical Analysis and Results

5.1 Measurement Model

Energy-saving motivations, as well as two constructs for controls, were inferred by exploratory factor analysis. We assessed the measurement model to confirm the reliability and convergent and discriminant validity of these constructs.[3] In addition, we conducted testing for a possible common method bias. Estimated testing results are reported in Appendix B. First, we checked the reliability of the measurement model by testing Cronbach's alphas and the composite reliability of all constructs except energy-saving behaviors. All factors show high reliability, with reliability measures greater than 0.7. An exploratory factor analysis of reflective measures shows that the loadings of all items on their own constructs are greater than 0.6 and the loadings of other constructs, indicating a sufficient level of convergent and discriminant validity for the measurement model (Hair et al., 2006).

Additionally, we checked validity through the average variance extracted (AVE) (Fornell & Larcker, 1981). We found that all AVEs are higher than 0.5, and the square roots of the AVEs are greater than the interconstruct correlations (the correlation matrix is provided in Appendix A), demonstrating convergent and discriminant validity (Fornell & Larcker, 1981). We also carried out a multicollinearity test for these variables by including all control variables and found that the estimated variance factors (VIFs) are all below 2, implying sufficient orthogonality.

In this study, we consider energy-saving behavior to be a formative construct since each indicator of energy-saving behavior contributes separately to reducing energy consumption, and indicators are not interchangeable with each other (Petter et al., 2007). To assess the formative measurement model, we checked the indicator-level and construct-level validity. For all items in this construct, the weight score is significant, and the VIF is below 3, confirming the validity of formative indicators (Petter et al., 2007). The interconstruct correlations are less than 0.7, further supporting the construct validity (Henseler, 2009).

Finally, we examined a possible common method bias by conducting Harman's single-factor test (Podsakoff et al., 2003). We found that the first factor captured only 22.3% of the variance in data, indicating that no single factor explains most of the variance. In addition, following the recommendation in Liang et al. (2007), we estimated a partial least square (PLS) model with a common method factor and calculated each indicator's variances, as explained by the principal construct and the method. This analysis dealt with energy-saving behavior, a formative construct, similar to a reflective construct to ensure the interpretability of the results (Herath & Rao, 2009). The results show that the average variance of indicators explained by the construct is 0.570, while the average variance explained by the method is 0.005. The ratio between the two is 114:1. Furthermore, we found no method factor loading to be statistically significant. For these reasons, we conclude that common method bias does not threaten the validity of our study.

5.2 SMT Adoption, Energy-Saving Motivations, and Energy-Saving Behaviors

5.2.1 Identification

To assess how households' energy consumption behaviors are associated with the adoption of SMT, we compared the energy-saving behaviors (ESB) of SMT adopters with those of non-adopters. The estimated model is as follows:

$$\text{ESB}_i = \alpha + \beta_1 \cdot \text{SMT Adoption}_i + \beta_{2-4} \cdot \text{SMT Adoption}_i \cdot X_{1-3,i} + \beta_{5-7} \cdot X_{1-3,i} + \mathbf{Z}_i \cdot \boldsymbol{\gamma} + \delta_i^t + \varepsilon_i, \quad (1)$$

where $X_{1-3,i}$ denotes a vector of energy-saving motivations; SMT Adoption_i is 1 if household i has smart meters, and 0 otherwise; $\mathbf{Z}_i$ is a vector of control variables; δ_{it} denotes a set of group-specific time fixed effects based on the sample selection criteria; and ε_i is an error term. All regression models are weighted by the inverse of the likelihood with which each individual is sampled.[4]

[3] Since we relied on a government-led pre-run survey, there are some single-item constructs. As we were able to apply an exploratory factor analysis and a multicollinearity test to these variables, we conducted these tests and found valid results, as reported in Appendix B2. We also provide conceptual validation of these constructs in Appendix B2. Remaining limitations are discussed in the last section.

[4] Since our sample is nationally representative, conditional on being weighted by this inverse of likelihood, we used the weighted regression as our main identification model. However, some papers suggested that the standard unweighted estimator on the stratified sample is consistent if the stratification is based on exogenous variables only (Solon et al., 2015) and it is more efficient than the weighted estimator (Wooldridge, 1999). Thus, we also estimated the unweighted regression and obtained qualitatively similar results. The estimated results are available upon request.

In Equation 1, the subscript of β between 1 and 4 indicates a hypothesis that the coefficient formally tests. For instance, if the estimated β_1 is positive and statistically significant, we can conclude that H1 is supported. Note that β_1 indicates the average effect of SMT adoption on energy-saving behaviors even in the presence of β_{2-4} (i.e., interaction terms), due to the normalization of independent variables. $\mathbf{Z}_i$ controls for household heterogeneity that might affect energy-saving behaviors. δ_i^t captures a group-specific flexible time trend that might affect adopters and non-adopters simultaneously (Antecol et al., 2018). Specifically, groups are defined by the sample selection criteria of this survey: sex, age, social grade, region, and housing tenure. For each of these variables, each level has its own year fixed effects, resulting in 85 coefficients.

5.2.2 Results

We report the estimated results in Table 4 and visualize the interaction effects in Figure 2. We found that the coefficients of SMT adoption are positive and statistically significant at the 1% level across all models, supporting H1. Based on the full model in Column 5, SMT adoption is associated with an approximately 0.20 standard deviation increase in energy-saving behaviors. The second and fifth columns suggest that the relationship is negatively moderated by concern about saving energy, supporting H2. However, we found no significant moderating effect of concern about national energy on the relationship between SMT adoption and energy conservation. Hence, we conclude that H3 is not supported. In line with H4, we found that concern about climate change positively moderates the relationship.

We also found that the estimated coefficients for direct effects of all saving motivations are positive and statistically significant at the 1% level, suggesting that they are significant predictors of energy-saving behaviors. Among these energy-saving motivations, concern about saving energy is the strongest predictor of energy-saving behaviors. Specifically, a one standard deviation rise in this motivation leads to a 0.28 standard deviation improvement in saving behaviors. It is worth noting that concern about climate change and concern about national energy are also significant predictors, even after controlling for other motivations, household characteristics, and group-specific year fixed effects. These results are in line with existing studies suggesting that residential consumers are substantially concerned about the carbon footprint of energy usage and the collective benefits of saving energy (Martinsson et al., 2011; Poortinga et al., 2004; Warkentin et al., 2017).

5.3 Moderating Effects of Technology Usage Intensity

To examine the hypothesized moderating effects of SMT usage intensity, we estimated the following equation:

$$\begin{aligned}&\mathrm{ESB}_i = \alpha + \beta_1 \cdot \text{SMT Adoption}_i + \beta_2 \cdot \\ &\text{SMT Adoption}_i \cdot \\ &\text{Monitoring at Least Occasionally}_i + \beta_3 \cdot \\ &\text{SMT Adoption}_i \cdot \text{Monitoring Everyday}_i + \beta_{4-6} \cdot \\ &X_{1-3,i} + \mathbf{Z}_i \cdot \boldsymbol{\gamma} + \delta_i^t + \varepsilon_i,\end{aligned} \tag{2}$$

where $\text{Monitoring at Least Occasionally}_i$ is 1 if the household looks at the display at least occasionally, and 0 otherwise; $\text{Monitoring Everyday}_i$ is 1 if the household looks at the display every day, and 0 otherwise; other variables are the same as defined in Equation 1. Since some SMT adopters decided to adopt alternative channels such as an online service, and their monitoring behaviors are not reported, we excluded such households from our analysis.

According to H5a, β_2 will be positive and statistically significant. β_3 is the marginal effect of the increased usage intensity from occasionally monitoring to doing so every day. Although it is not easy to quantitatively compare usage intensity using these measures, we can safely postulate that these responses imply a significant difference in monitoring frequency. Therefore, if β_3 is not positively significant, we can conclude that H5b is supported.

The estimated results are shown in Table 5 and visualized in Figure 3. The findings suggest that β_2 is positive and significant, supporting H5a. Notably, we found that the coefficient of SMT adoption is not significant economically and statistically, suggesting that SMT adoption facilitates energy-saving behaviors only through providing information. The last column suggests that β_3 is slightly negative and statistically insignificant, indicating that higher usage intensity does not lead to more savings, in line with H5b. These results suggest that the information gain from IHD monitoring reaches the maximum level quickly, and excessive usage does not induce further energy-saving behaviors.

5.4 Robustness Checks

5.4.1 Matching Approach

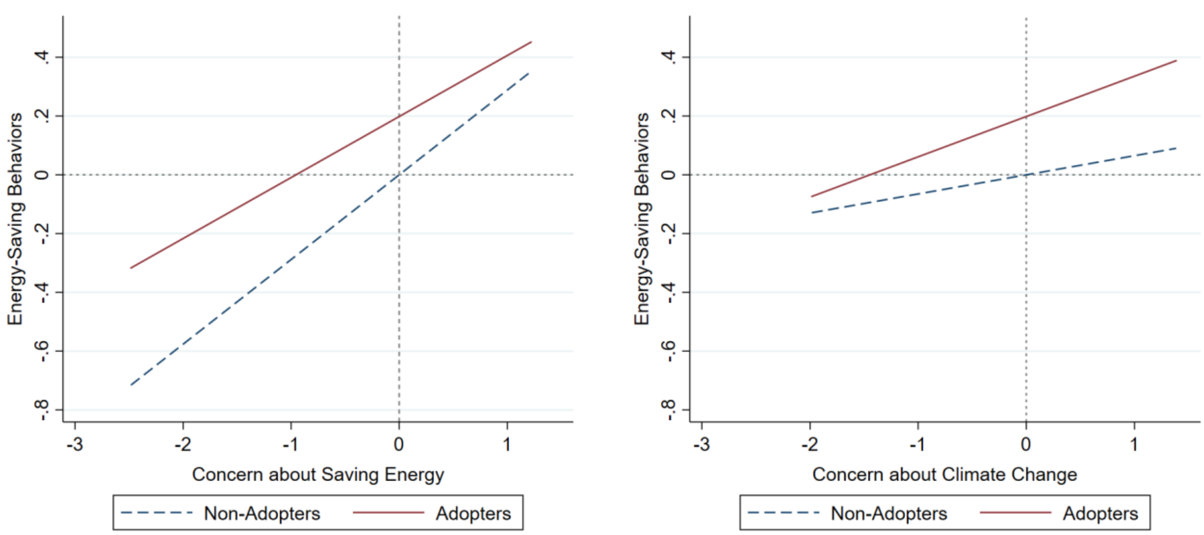
To address the potential bias that might arise from an imbalance between adopters and non-adopters, we used propensity score matching (PSM), which finds a pair of treated and control households according to the proximity of their propensity scores (Rosenbaum & Rubin, 1983).

Table 4. SMT Adoption, Energy-Saving Motivations, and Energy-Saving Behaviors

Dependent variable	**Energy-saving behaviors**				
Specifications	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Adoption and moderating effects					
SMT adoption (H1)	0.191***	0.199***	0.191***	0.188***	0.198***
	(0.0322)	(0.0329)	(0.0321)	(0.0322)	(0.0329)
× Concern about saving energy (H2)		-0.0626*			-0.0806**
		(0.0352)			(0.0364)
× Concern about national energy (H3)			0.0401		0.0277
			(0.0323)		(0.0346)
× Concern about climate change (H4)				0.0677**	0.0721**
				(0.0319)	(0.0343)
Direct effects of moderators					
Concern about saving energy	0.276***	0.285***	0.277***	0.277***	0.288***
	(0.0128)	(0.0135)	(0.0127)	(0.0128)	(0.0136)
Concern about national energy	0.0475***	0.0474***	0.0418***	0.0472***	0.0432***
	(0.0132)	(0.0132)	(0.0141)	(0.0132)	(0.0142)
Concern about climate change	0.0757***	0.0756***	0.0755***	0.0659***	0.0650***
	(0.0127)	(0.0127)	(0.0127)	(0.0136)	(0.0137)
Household-specific controls	Included	Included	Included	Included	Included
Group-specific year fixed effects	Included	Included	Included	Included	Included
Observations	8,125	8,125	8,125	8,125	8,125
R-squared	0.144	0.144	0.144	0.145	0.145

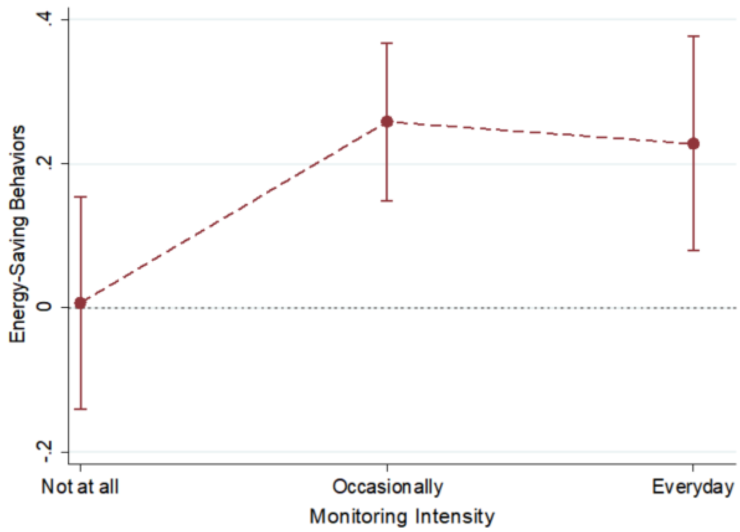
Note: Robust standard errors are in parentheses. $*p < 0.10$; $**p < 0.05$; $***p < 0.01$. All estimates are weighted by the inverse of the likelihood with which each individual is sampled. Group-specific year fixed effects indicate that each level of sex, age, social grade, region, or housing tenure has its own year fixed effects, resulting in 85 coefficients.

(a) Concern about Saving Energy **(b) Concern about Climate Change**



Note: All variables are standardized for ease of interpretation. We set the expected level of energy-saving behaviors with the zero value of each moderator as the baseline for each graph. Each line connects the minimum and the maximum points of corresponding moderating variables.

Figure 2. Moderating Effects of Energy-Saving Motivations



Note: All variables are standardized for ease of interpretation. Each point indicates the estimated effect on energy-saving behaviors by monitoring intensity, which is calculated by the coefficients shown in Column 3 in Table 5. The range denotes a 95% confidence interval for each coefficient.

Figure 3. Monitoring Intensity and Impact on Energy-Saving Behaviors

Table 5. SMT Usage Intensity and Energy-Saving Behaviors

Dependent variable	**Energy-saving behaviors**		
Specifications	**(1)**	**(2)**	**(3)**
SMT adoption and usage intensity			
SMT adoption	0.182***	0.00686	0.00686
	(0.0402)	(0.0753)	(0.0753)
× Monitoring at least occasionally (H5a)		0.241***	0.251***
		(0.0867)	(0.0921)
× Monitoring every day (H5b)			-0.0305
			(0.0920)
Household-specific controls	Included	Included	Included
Group-specific year fixed effects	Included	Included	Included
Observations	7,644	7,644	7,644
R-squared	0.147	0.148	0.148

Note: Robust standard errors are in parentheses. *p < 0.10; **p < 0.05; ***p < 0.01. All estimates are weighted by the inverse of the likelihood with which each individual is sampled. Group-specific year fixed effects indicate that each level of sex, age, social grade, region, or housing tenure has its own year fixed effects, resulting in 85 coefficients. We exclude SMT adopters who did not adopt in-home displays (IHDs), given that they adopted alternative channels such as online webpages and television.

Reducing high-dimensional covariates to the probability of being treated enables researchers to easily compare similarity across subjects (Dehejia & Wahba, 2002); thus, this method has been widely adopted by the extant IS literature (e.g., Xu et al., 2017; Son et al., 2020).[5]

We utilized one-to-one matching without replacement under various caliper sizes from 0.001 to 0.0001 times the standard deviation of the propensity scores, which are sufficiently small or conservative (Xu et al., 2017; Son et al., 2020). To evaluate the validity of PSM, we

[5] Alternative approaches might also be applied to reduce the sample imbalance. For instance, Mahalanobis distance matching, which utilizes the Mahalanobis distance (similar to the Euclidean distance), also relies on a reduced value of (dis)similarity and yields qualitatively similar results (see Appendix C). Coarsened exact matching (Iacus et al., 2012), which treats continuous variables like categorical variables by utilizing coarsened values, has also been used recently in academic studies. This method assigns each observation to a stratum, a combination of coarsened values, and the number of strata exponentially increases in the number of variables and that of coarsened values. Since our dataset contained several control variables, including categorical variables that cannot be coarsened, the number of potential strata exploded as a result. Specifically, this matching algorithm assigned our 8,125 observations to 8,119 unique strata, failing to match the control and treatment groups. For these reasons, we adopted propensity score matching, which allows researchers to utilize high dimensional data with a simplified scalar value—the likelihood of being assigned to the treatment (Dehejia & Wahba, 2002).

compared the distributions of propensity scores and the covariate balance before and after matching (Caliendo & Kopeinig, 2008). The testing results show that the two groups are statistically indistinguishable in terms of distributions of propensity scores and covariate means (see Appendix C for details).

Table 6 shows the matched estimators of Equation 1, suggesting that our hypotheses concerning the average effect and heterogeneity by saving motivation are not sensitive to sample selection criteria. Notably, we observed that more conservative criteria (i.e., smaller caliper sizes) led to more robust support for H4, further supporting the robustness of our findings. In Table 7, we report the moderating effects of usage intensity estimated based on matched samples. The results are consistent with those in Table 5 across all caliper sizes. In sum, our results are unlikely to have been spuriously driven by the imbalance between adopters and non-adopters.

5.4.2 Placebo Tests

To further ascertain that our estimates are not spurious, we performed two placebo tests, which aim to examine whether or not a similar size and significance of effects are observed under a fake treatment instead of the real treatment. If similar effects are observed from the fake treatment, we can conclude that our main treatment effects are drawn spuriously.

First, we conducted a random implementation test, reassigning the adoption indicators at random in our data (Burtch et al., 2018). Second, we utilized the adoption of solar thermal panels as a fake treatment. In Appendix D, we describe the motivations, procedures, and results of these tests, suggesting that our findings are very unlikely to be attributable to unobservable determinants of SMT adoption.

Table 6. Matched Sample and Testing Results of H1-H4

Dependent variable	**Energy-saving behaviors**					
Caliper sizes	**0.001**		**0.005**		**0.0001**	
Specifications	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Adoption and moderating effects						
SMT adoption (H1)	0.161***	0.171***	0.160***	0.167***	0.148***	0.147***
	(0.0405)	(0.0411)	(0.0410)	(0.0416)	(0.0438)	(0.0441)
× Concern about saving energy (H2)		-0.101**		-0.110**		-0.122**
		(0.0457)		(0.0463)		(0.0496)
× Concern about national energy (H3)		0.00254		0.00142		-0.0163
		(0.0459)		(0.0465)		(0.0502)
× Concern about climate change (H4)		0.0715		0.0810*		0.110**
		(0.0465)		(0.0475)		(0.0509)
Household-specific controls	Included	Included	Included	Included	Included	Included
Group-specific year fixed effects	Included	Included	Included	Included	Included	Included
Observations	2,228	2,228	2,158	2,158	1,896	1,896
R-squared	0.177	0.180	0.182	0.186	0.190	0.195

Note: Robust standard errors are in parentheses. *p < 0.10; **p < 0.05; ***p < 0.01. Group-specific year fixed effects indicate that each level of sex, age, social grade, region, or housing tenure has its own year fixed effects, resulting in 85 coefficients.

Table 7. Matched Sample and Testing Results of H5

Dependent variable	**Energy-saving behaviors**		
Caliper sizes	**0.001**	**0.005**	**0.0001**
Specifications	**(1)**	**(2)**	**(3)**
SMT adoption and usage intensity			
SMT adoption	0.0953	0.102	0.106
	(0.0810)	(0.0813)	(0.0831)
× Monitoring at least occasionally (H5a)	0.216**	0.214**	0.207**
	(0.0892)	(0.0893)	(0.0916)
× Monitoring every day (H5b)	-0.0331	-0.0209	0.00836
	(0.0908)	(0.0914)	(0.0973)
Household-specific controls	Included	Included	Included
Group-specific year fixed effects	Included	Included	Included
Observations	1,340	1,320	1,224
R-squared	0.204	0.204	0.211

Note: Robust standard errors are in parentheses. *p < 0.10; **p < 0.05; ***p < 0.01. Group-specific year fixed effects indicate that each level of sex, age, social grade, region, or housing tenure has its own year fixed effects, resulting in 85 coefficients. We exclude SMT adopters who did not adopt in-home displays (IHDs), given that they adopted alternative channels such as online webpages and television.

6 Discussion and Conclusion

Building on CDT, we develop hypotheses concerning the contingent effects of SMT adoption on energy-saving behaviors depending on energy-saving motivations and usage intensity. We tested our hypotheses based on a rich household dataset in the UK during the national rollout program between 2012 and 2016. Throughout the analysis, we found supporting evidence for most of our hypotheses. Our main findings suggest that SMT adoption is less likely to increase the energy-saving behaviors of residential consumers who are more concerned about saving energy. The results may indicate that SMT does not provide such customers with new information that contradicts their beliefs about their energy consumption. Specifically, these consumers are likely to have already made an effort to save energy; further, they likely check their bills frequently and are thus already more informed about energy usage and costs (Gerarden et al., 2017; Sallee, 2014; Sexton, 2015). Hence, feedback on energy consumption may not deliver new information for such consumers.

Conversely, we show that the impact of SMT adoption on energy-saving behaviors is intensified with consumers who are more concerned about climate change. This result is consistent with our intuition that higher altruistic motivations will induce a more intense feeling of hypocrisy when consumers face the belief-consumption gap. People who are concerned about climate change are not necessarily more attentive to energy bills since the monetary value of energy consumption is more closely associated with egoistic rather than altruistic motivations (Wang et al., 2018). We thus conjecture that such consumers can benefit from information regarding their own energy usage, which may lead to these consumers recognizing a substantial inconsistency between the feedback information and their prior beliefs about their consumption behaviors, which may thus result in energy conservation by these consumers. However, this finding should be interpreted with caution, as the statistical significance was slightly unstable across matching criteria although the significance increased as we selected more conservative caliper sizes.

While most of our hypotheses are supported, we found no evidence supporting the moderating effect of concern about national energy on the relationship between SMT adoption and energy-saving behaviors. Given that concern about national energy is a valid predictor of energy-saving behaviors separate from other covariates, we conjecture that this concern might be positively associated with prior knowledge of one's own household consumption. Specifically, consumers who are more concerned about national energy might already be aware of their own consumption, as information on national energy issues, energy-saving tips, and relevant news is delivered through similar channels (e.g., *The Guardian*'s "Energy" section). If such concern facilitates their knowledge, it might offset the possible cognitive dissonance from their altruistic motivation and feelings of hypocrisy (Dickerson et al., 1992; Sallee, 2014; Sexton, 2015).

Importantly, we show that SMT usage intensity—i.e., monitoring intensity—is positively associated with energy-saving behaviors, but the relationship is nonlinear. Monitoring IHDs every day does not translate to additional savings, compared with monitoring IHDs occasionally. These results may indicate that consumers do not obtain more useful information from daily monitoring than from weekly monitoring, possibly because energy-consumption patterns are noisy and periodic within a day and even within a week (Kwac et al., 2014; Eom et al. 2020). If so, relatively infrequent but regular usage of SMT could be more effective than frequent but irregular usage in reducing energy consumption.

6.1 Implications for Research

Our study provides several important implications for the literature on sustainable technology adoption. While previous studies have mainly focused on drivers of sustainable IT adoption (Gholami et al., 2013; Marett et al., 2013; Warkentin et al., 2017), there is a lack of studies concerning the impact on resource conservation of households' sustainable IT adoption. Several studies have attempted to uncover how information feedback changes resource consumption behaviors. However, only a few have examined heterogeneous effects across households (Carroll et al., 2014; Asensio & Delmas, 2015; Tiefenbeck et al., 2018). Moreover, we are aware of little research that provides a theoretical discussion to unravel this heterogeneity. Motivated by this important gap, our study contributes to this literature stream by showing how the cognitive dissonance mechanism explains the heterogeneous impact of SMT adoption on energy-saving behaviors, depending on energy-saving motivations and technology usage intensity, and providing empirical evidence from rich data over five consecutive years during the rollout program in the UK. Our findings reveal the significance and consequences of heterogeneous responses to sustainable technology adoption and provide directions for future studies in this burgeoning research stream.

This study also expands our understanding of how CDT can provide insights into pro-environmental behaviors. Previous studies have used CDT to explain motivations for pro-environmental behavior and to develop interventions to boost these behaviors (Dickerson et al., 1992; Thøgersen, 2004; Stone & Fernandez, 2008), but little research has investigated moderating factors of the cognitive dissonance induced by technology adoption. Our study demonstrates that technology-induced saving behaviors are significantly moderated by energy-saving motivations and technology usage intensity, as hypothesized by CDT. These findings furnish the theoretical foundations for understanding the underlying mechanisms of households' sustainable IT regarding information feedback and suggest that CDT might be applied to explain heterogeneous effects in many other contexts in which information artifacts are introduced to fill information gaps rather than to provide alternatives for existing products or services.

In addition, our research provides the first empirical evidence that the use of sustainable IT increases environmental outcomes but the additional gain decreases with usage intensity. This suggests that technology usage after adoption is a necessary condition for altering target behaviors, as expected, but seeking to increase usage intensity may have a limited impact on target behaviors. This echoes the caveat of assuming that successful technology adoption and usage will lead to success in organizational or governmental outcomes, as stressed in the extant literature (Venkatesh et al., 2003; Venkatesh et al., 2016; Srivastava et al., 2016).

6.2 Implications for Firms and Policymakers

In this study, we identify several implications for energy utility firms and policymakers. Our results show that the higher penetration rates of SMT do not ensure the success of smart energy systems. For instance, the positive impact of SMT adoption on energy-saving behaviors is less prominent for households that are more concerned about saving energy. Although they could be receptive to SMT, their behaviors are unlikely to change, possibly because they have already been informed and have reduced their energy consumption before adopting SMT.

Given this significant heterogeneity across energy-saving motivations, utility firms should carefully consider prioritizing targeting based on expected benefits from each adopter as well as the adoption intention. For instance, they could potentially operate more effectively by focusing on relatively less energy-conscious consumers who are less attentive to their own energy consumption. Pro-environmental households are also viable targets. Given that SMT has been advertised by the government and press mostly as a vehicle for saving money (European Commission, 2018b; Nhede, 2019), shifting the focus of promotion from energy bills to climate change may induce a substantial change in consumer responses.

Importantly, if households do not expect heterogeneous effects, the performance gap might lead to disconfirmation concerning technology performance expectations, which could result in negative experiences and emotions (Marikyan et al., 2020). In the end, rollout programs were criticized for their actual benefits with respect to energy savings (Brignal, 2016; Meadows, 2017). These undesirable outcomes may be partially attributed to the selection of participants in the smart grid rather than the technology per se, as suggested by our findings.

Remarkably, our findings suggest that additional energy conservation can be achieved by convincing inactive adopters to monitor IHDs at least occasionally. However, attempting to motivate more frequent monitoring is unlikely to induce behavioral changes, as the information gains from SMT adoption reach the maximum level quickly as usage intensity increases. Given this, utility firms might target inattentive households for promoting monitoring behaviors, whereas they may consider attentive households as targets for pricing-based policies, as these consumers have already reached their optimal consumption under given pricing schemes.

6.3 Limitations and Future Research

This study is not without limitations, some of which may pave the way for future research. First, our study examines the rollout policy in only one country. Although the UK is one of the most active countries in implementing smart grid infrastructure, to further validate our findings, future research should take regional and governmental differences in rollout programs into account. For instance, the UK government subsidized residential consumers and provided SMT for free. Therefore, the adoption pattern might substantially differ in the presence of monetary costs for adoption. An empirical investigation of this possibility could offer valuable insights for different market environments.

Second, our analysis on the impact of smart meter adoption relies on a single outcome, energy-saving behaviors, rather than actual energy consumption levels. In this vein, future studies could contribute to the literature in several ways. For example, they could enhance the internal validity of findings by adopting actual measurements of energy use instead of self-reported measures. Researchers could also examine more diverse dimensions of energy conservation, such as load shifting and peak management, which may provide further implications for utilities and policymakers (Houde et al., 2013; Schleich et al., 2017). Related to this, due to the nature of a government-led pre-run survey, we also relied on some single-item constructs. While we provided several justifications to produce valid results, measurement errors may nevertheless remain. Future research considering multi-item constructs, alternative measures, or objective data could enhance the reliability of our findings.

Third, we cannot completely rule out the possibility that unobservable factors affect our results. We have demonstrated that our results are unlikely to present spurious relationships through including several control variables, using propensity score matching based on observables and falsification tests. However, these results should be interpreted with caution because unobservable factors such as economic considerations and social influence have not been fully considered.

6.4 Concluding Remarks

The present work shows that the rollout of SMT can indeed contribute to greenhouse gas reductions and climate change mitigation by inducing households to engage in energy-saving behaviors. Importantly, we establish that such technology-induced behaviors are highly contingent upon individuals' energy-saving motivations and technology usage intensity, as derived from a novel application of cognitive dissonance theory. This research is expected to facilitate future research devoted to understanding the heterogeneous responses to sustainable technology adoption, which have been largely underexplored. From a practical perspective, energy suppliers and policymakers can benefit from our findings through the development of effective technology rollout and promotion strategies.

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Appendix A: Description of Control Variables

Concern about daily expenses: This construct is measured by three items rated on a 4-point scale from 1 = *Not at all worried* to 4 = *Very worried*. These items measure the level of worry about expenses related to "food and other household shopping," "transport, including petrol/diesel and public transport costs," and "mortgage or rent payments," which are not directly associated with household energy consumption. So, the construct captures a household's general concern for outgoings that might be indirectly related to its sensitivity to energy expenses.

Attitude toward renewable energy: In this paper, attitude toward renewable energy refers to the extent to which a household supports the use of renewable energy. This construct was measured by five items for on-shore wind, biomass, off-shore wind, wave and tidal, and solar, rated on a 5-point Likert scale from 1 = *Strongly oppose* to 5 = *Strongly support*.

Age: Age of respondent is rated on a 6-point scale. Previous works have suggested that older people are more likely to have pro-environmental attitudes and save household energy (Barr et al., 2005; Martinsson et al., 2011). Age has also been revealed to have substantial explanatory power on technology adoption because younger individuals tend to adopt new technology more voluntarily and are less sensitive to perceived risks, social norms, and traditions, compared to older individuals (Morris et al., 2005).

Female: This variable indicates 1 if a respondent is female, and 0 otherwise. In the context of energy and environmental issues, gender has been suggested as a main factor affecting pro-environmental decisions. Previous studies have shown that women are more likely to perceive environmental risks to be higher (Bord & O'Connor, 1997) and participate in voluntary actions to reduce energy consumption than men (O'Connor et al., 1999). The extant literature on technology adoption has also suggested that women and men significantly differ in terms of technology acceptance and use. For example, women consider perceived ease of use to a greater extent than men in deciding whether to use new technologies, both in the short- and long-term, whereas the opposite trend was found in regard to perceived usefulness (Venkatesh & Morris, 2000). Pascual-Miguel et al. (2015) showed that female shoppers are less likely to purchase digital goods and respond to product risks more sensitively than male shoppers regarding online websites.

Rural: To capture differences in lifestyle and regional differences, we controlled for whether a household is in a rural area or in an urban area, formally, defined as 1 if a household resides in a rural area, and 0 otherwise. Prior works have shown that people living in rural areas show more pro-environmental orientation and environmental responsibility (Berenguer et al., 2005), and tend to save more energy (Martinsson et al., 2011) compared to residents in urban areas. Forman et al. (2005) showed that the diffusion of information technology substantially differs between urban and rural areas.

Household size: This is defined as the number of people living in the household. The variable is a count variable up to five people, and a household of more than five people is coded as 5. Household size is also a factor that could affect household decisions in a variety of contexts, such as product choices and labor market participation (Flurry, 2007; Heitmueller, 2007).

Having a child: We define having a child as a dichotomous variable that is denoted as 1 if there is at least one child under sixteen in household, and 0 otherwise. In many contexts, it has been suggested that households' behaviors and decision-making are affected by interactions between children and parents. For example, energy education and behavior programs for children are revealed to affect parents' energy-saving behaviors positively, as well as children's own behaviors (Boudet et al., 2016). However, Martinsson et al. (2011) showed that the mere presence of children does not guarantee more energy-saving behaviors. Considering technology adoption, it has been shown that young children are likely to be more "tech-savvy" than adults (Mallan et al., 2010); thus, they may have a substantial influence on a household's adoption decisions regarding new technologies via information spillover (Belo et al., 2016).

Income reported: In DECC's survey, nearly 30% of our sample did not report their household income. Therefore, we included this dummy variable indicating whether or not respondents reported their household income. Given that reporting behaviors might be associated with potential risks of releasing personal information, we considered not reporting income to imply more concern about information privacy. In other words, households that reported their income may have less concern about information privacy.

Income reported × Amount: This variable indicates income amount measured by a 5-point item, where a respondent did not refuse to report their income. Martinsson et al. (2011) found that household income is negatively associated with saving energy on heating and hot water. Chen et al. (2017) suggested a positive relationship between income and intention to adopt smart meters, but the magnitude was not remarkable.

Social class: In the UK, households are classified based on the chief income earner's occupation following the National Readership Survey (NRS) social grades. The classification system consists of six social classes. For instance, individuals with managerial, administrative, and professional jobs are classified as A or B, and manual workers are categorized as C2 or D. There is a strong association between income and social grade, but income is not part of the classification. Social class also has strong discriminatory power in many contexts such as media consumption (National Readership Survey, 2018). In our analysis, each class was included as a dummy variable.

Housing tenure: Housing tenure denotes the financial arrangements under which the household has the right to live in a house or apartment. In this study, there are five types of housing tenure, and each of them were included as a dummy variable. Research suggests that the type of household ownership has explanatory power on energy-saving behavior in that home ownership leads to a larger investment in energy-efficient assets (Martinsson et al., 2011).

Table A1. Summary Statistics of Categorical Variables

Variables	**Label**	**Frequency**	**Proportion (%)**
Social class	A	226	2.78
	B	1,245	15.32
	C1	2,149	26.45
	C2	1,585	19.51
	D	1,300	16
	E	1,620	19.94
Housing tenure	Being bought on mortgage	2,082	25.62
	Owned outright by household	2,277	28.02
	Rented from local authority	1,761	21.67
	Rented from private landlord	1,848	22.74
	Other	157	1.93

Appendix B: Measurements and Statistical Tests

Measurement Items and Model Estimates

Table B1. Measurement Items

Variables	Survey items		Scale
Energy-saving behaviors (ESB)	ESB1	Leave the lights on when you are not in the room. (negative)	1 Never 2 Occasionally 3 Quite often 4 Very often 5 Always
	ESB2	Boil the kettle with more water than you are going to use. (negative)	
	ESB3	Wash clothes at 30 degrees or lower. (positive)	
	ESB4	Try to keep rooms that you are not using at a cooler temperature than those you are using. (positive)	
	ESB5	Leave the heating on when you go out for a few hours. (negative)	
Concern about saving energy (CSE)	CSE1	How much thought, if any, would you say you give to saving energy in your home?	1 None at all 2 Not very much 3 A fair amount 4 A lot
Concern about national energy (CNE)	CNE1	UK supplies of fossil fuels not being sufficient to meet the UK's demand for them.	1 Not at all concerned 2 Not very concerned 3 Fairly concerned 4 Very concerned
	CNE2	The UK becoming too dependent on energy from other countries.	
	CNE3	The UK not investing fast enough in alternative sources of energy.	
	CNE4	The UK not developing technology to use existing sources of fossil fuels sufficiently.	
Concern about climate change (CCC)	CCC1	How concerned, if at all, are you about climate change, sometimes referred to as 'global warming'?	1 Not at all concerned 2 Not very concerned 3 Fairly concerned 4 Very concerned
Concern about daily expenses (DCE)	CDE1	As far as you know, how worried has the person in your household who is responsible for paying for these been about this over the last three months? Food and other household shopping	1 Not at all worried 2 Not very worried 3 Fairly worried 4 Very worried
	CDE2	Transport, including petrol/diesel and public transport costs	
	CDE3	Mortgage or rent payments	
Attitude toward renewable energy (ARE)	ARE1	Generally speaking, do you support or oppose the use of the following renewable energy developments? On-shore wind	1 Strongly oppose 2 Oppose 3 Neither support nor oppose 4 Support 5 Strongly support
	ARE2	Biomass—this includes any plant or animal base material such as wood, specially grown energy crops, and other organic wastes that can be used in the process of creating energy.	
	ARE3	Off-shore wind	
	ARE4	Wave and tidal	
	ARE5	Solar	

Table B2. Exploratory Factor Analysis

Items	Constructs				
	CSE	CNE	CCC	CDE	ARE
CSE1	**0.978**	0.111	0.075	0.054	0.086
CNE1	0.017	**0.838**	0.077	0.100	0.107
CNE2	0.087	**0.838**	0.036	0.048	0.093
CNE3	0.035	**0.824**	0.184	0.067	0.177
CNE4	0.036	**0.850**	0.039	0.097	0.087
CCC1	0.085	0.264	**0.922**	0.060	0.169

CDE1	0.056	0.115	0.008	**0.876**	-0.006
CDE2	0.065	0.145	-0.031	**0.830**	0.023
CDE3	-0.052	0.003	0.092	**0.826**	0.032
ARE1	-0.055	-0.025	0.177	0.067	**0.785**
ARE2	0.074	0.149	-0.063	0.009	**0.666**
ARE3	-0.015	0.069	0.118	0.006	**0.839**
ARE4	0.078	0.166	-0.013	-0.060	**0.779**
ARE5	0.047	0.116	0.054	0.048	**0.758**

Table B3. Descriptive Statistics and Reliability Measures for Constructs

Variables	**CSE**	**CNE**	**CCC**	**CDE**	**ARE**	**ESB**
Mean	3.024	2.911	2.782	2.147	3.962	3.634
SD	0.796	0.715	0.875	0.824	0.698	0.735
Cronbach's alpha	n.a.	0.879	n.a.	0.808	0.833	n.a.
Composite reliability	n.a.	0.916	n.a.	0.783	0.882	n.a.
Average variance extracted (AVE)	n.a.	0.733	n.a.	0.570	0.602	n.a.
Square roots of AVE	n.a.	0.856	n.a.	0.755	0.776	n.a.

Table B4. Weight Scores of Formative Construct

Construct		**Weight score**	***t*-statistics**	**VIF**
Energy-saving behaviors (ESB)	ESB1	0.264295	7.33556***	1.142
	ESB2	0.316309	8.90287***	1.095
	ESB3	0.412317	12.6467***	1.040
	ESB4	0.597103	20.6934***	1.054
	ESB5	0.133137	3.60899***	1.084

Note: *$p < 0.5$; **$p < 0.01$; ***$p < 0.001$.

Table B5. Common Method Bias Analysis

Construct	**Indicator**	**Substantive factor loading (R1)**	***R*-sq.**	**Method factor loading (R2)**	***R*-sq.**
Concern about saving energy (CSS)	CSE	1		0	
Concern about national energy (CNE)	CNE1	0.864***	0.746	-0.011	0.000
	CNE2	0.883***	0.780	-0.048	0.002
	CNE3	0.774***	0.599	0.113	0.013
	CNE4	0.904***	0.817	-0.055	0.003
Concern about climate change (CCC)	CCC	1		0	
Concern about daily expenses (CDE)	DEC1	0.885***	0.783	0.002	0.000
	DEC2	0.833***	0.694	0.038	0.001
	DEC3	0.832***	0.692	-0.042	0.002
Attitude toward renewable energy (ARE)	ARE1	0.859***	0.738	-0.101	0.010
	ARE2	0.630***	0.397	0.059	0.003
	ARE3	0.875***	0.766	-0.038	0.001
	ARE4	0.762***	0.581	0.041	0.002
	ARE5	0.735***	0.540	0.051	0.003
Energy-saving behaviors (ESB)	ESB1	0.714***	0.510	-0.051	0.003
	ESB2	0.633***	0.401	-0.041	0.002
	ESB3	0.310	0.096	0.116	0.013
	ESB4	0.418	0.175	0.124	0.015
	ESB5	0.617***	0.381	-0.057	0.003
SMT adoption	Adoption	1		0	
Average			0.570		0.005

Note: *$p < 0.5$; **$p < 0.01$; ***$p < 0.001$.

Table B6. Multi-Collinearity Diagnostics

Variables	VIF	VIF-sq.	Tolerance	*R*-squared
Concern about saving energy	1.10	1.05	0.9114	0.0886
Concern about national energy	1.31	1.14	0.7649	0.2351
Concern about climate change	1.25	1.12	0.8005	0.1995
Concern about daily expenses	1.29	1.13	0.7778	0.2222
Attitude toward renewable energy	1.18	1.09	0.8483	0.1517
Age	1.79	1.34	0.5601	0.4399
Female	1.04	1.02	0.9654	0.0346
Rural	1.02	1.01	0.9789	0.0211
Household size	1.93	1.39	0.5171	0.4829
Having a child	1.77	1.33	0.5661	0.4339
Income reported	2.21	1.49	0.4521	0.5479
Income reported × Amount	2.67	1.63	0.3743	0.6257
Social Class (A is baseline)				
Class B	5.59	2.36	0.1790	0.8210
Class C1	8.09	2.84	0.1236	0.8764
Class C2	6.83	2.61	0.1464	0.8536
Class D	6.25	2.50	0.1600	0.8400
Class E	7.53	2.74	0.1329	0.8671
Housing tenure (Being bought on mortgage is baseline)				
Owned outright by household	1.97	1.40	0.5077	0.4923
Rented from local authority	1.91	1.38	0.5237	0.4763
Rented from private landlord	1.71	1.31	0.5847	0.4153
Other	1.08	1.04	0.9277	0.0723
Year (2012 is baseline)				
2013	1.60	1.27	0.6233	0.3767
2014	1.57	1.25	0.6384	0.3616
2015	1.63	1.28	0.6140	0.3860
2016	1.72	1.31	0.5817	0.4183
Mean VIF	2.64			

Note: VIF denotes the variance inflation factor; VIF-sq. denotes the square of VIF; tolerance denotes (1 - *R*-squared), where *R*-squared is obtained by regressing a covariate on the other covariates.

Validation of Single-Item Constructs

Since we relied on a government-led pre-run survey, there are some inevitable limitations in the measurement, e.g., the adoption of a single item for some constructs. To address this concern, we first checked the statistical validity of these variables. We conducted an exploratory factor analysis by including single-item constructs. The results shown in Table B2 suggest that the single-item constructs, concern about saving energy and concern about climate change, are not substantially explained by other constructs. Therefore, we conclude that our single-item constructs are statistically valid. In addition, the variance inflation factor (VIF) reported in Table B6 suggests that these variables are clearly distinguished from other constructs and control variables (VIFs < 2).

Moreover, the constructs using a single-item measure in our research model were queried using an unambiguous and global question (concern about saving energy: “Level of thought given to saving energy in the home,” and concern about climate change: “How concerned, if at all, are you about climate change, sometimes referred to as ‘global warming’?”) to consider a general view of constructs (Sackett & Larson, 1990; Gorsuch & McPherson, 1989). These items were also asked to a wide range of populations to adjust the necessity of reducing the length of construct measures due to fatigue and time concerns (Fuchs & Diamantopoulos, 2009). In a similar vein, there are several constructs in the literature that use a single-item measure: for example, Wanous et al. (1997) showed the acceptability of single-item measures using the meta-analysis of job satisfaction. Taken together, despite the remaining possibility of measurement errors from using single-item constructs, our analysis can be considered acceptable.

Additionally, we provide additional support for the measurement of concern about climate change, suggesting that this single-item measure properly picks up the pro-environmental motivation to save energy in the SMT adoption context. Specifically, it has been regarded as a major environmental concern related to energy consumption. For instance, Noppers et al. (2016) examined the impact of environmental attributes on the adoption of smart energy meters. They used three items for the construct each of which asks CO_2 emission, global warming, and quality of environment, and noticeably, two of the three items (i.e., CO_2 emission and global warming) are directly associated with climate change. Because smart energy meters are related to the amount of energy consumption rather than the direct emission of toxic chemicals such as sulfur dioxide, the researchers focused on climate change rather than other aspects of the environment. Furthermore, this is consistent with the widespread notion among politics, businesses, and the public spheres (Deshmukh, 2015; Delta-EE, 2019). As expected, smart meters are considered a vital vehicle for tackling climate change among practitioners (Deshmukh, 2015). Importantly, when the environmental benefits of smart meters are considered, industry experts have focused heavily on a reduction in carbon emissions rather than immediate environmental benefits such as air quality (Delta-EE, 2019). For these reasons, we believe that our single-item measure of concern about climate change indeed captures the pro-environmental motivation to reduce energy consumption.

Appendix C: Matching Analysis and Balance Checks

Balance Checks for Propensity Score Matching

To ensure comparability of the treatment and control groups, we compared observable characteristics between the two groups. As reported in Table C1, these groups are significantly different in observables before matching, but these variables are indistinguishable after matching as shown in Table C2, Table C3, and Table C4, for caliper sizes of 0.001, 0.0005, and 0.0001, respectively. We also illustrate the plots of propensity score distributions before and after matching in Figure C1. It is clear that our matching approach decreases the differences in the distributions. We formally tested this argument by carrying out a Kolmogorov-Smirnov test and found that the differences in the distributions are statistically significant before matching ($p < 0.001$), but the differences become insignificant after matching across all caliper sizes ($p > 0.999$).

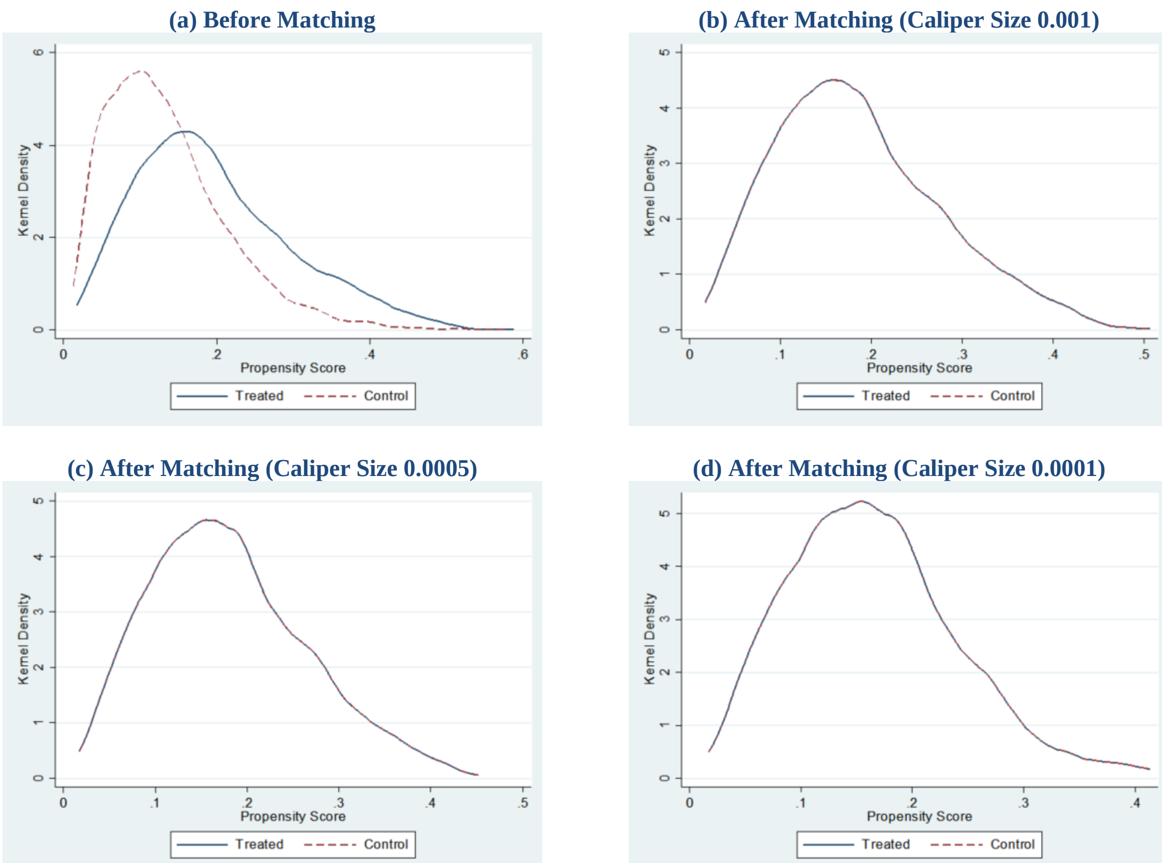

Figure C1. Kernel Density of Propensity Score Before Matching

Table C1. Comparisons of Means before Matching

	Before matching			
Variables	**Treated**	**Control**	***t*-statistic**	***p*-value**
Independent variables				
Concern about saving energy	0.135	-0.004	4.450	<0.001
Concern about national energy	-0.023	0.014	-1.200	0.232
Concern about climate change	0.008	0.019	-0.350	0.725
Control variables				
Concern about daily expenses	0.000	0.006	-0.190	0.849
Attitude toward renewables	0.030	0.028	0.080	0.933
Age	3.273	3.718	-8.130	<0.001
Female	0.502	0.537	-2.210	0.027
Rural	0.172	0.199	-2.190	0.029

Household size	2.822	2.546	6.780	<0.001
Having a child	0.404	0.277	8.830	<0.001
Income reported	0.789	0.707	5.720	<0.001
Income reported × Amount	1.741	1.656	1.690	0.092
Social class (A is baseline)				
Class B	0.129	0.157	-2.490	0.013
Class C1	0.242	0.268	-1.860	0.063
Class C2	0.198	0.195	0.310	0.753
Class D	0.181	0.156	2.140	0.032
Class E	0.228	0.195	2.610	0.009
Housing tenure (being bought on mortgage is baseline)				
Owned outright by household	0.210	0.292	-5.740	<0.001
Rented from local authority	0.311	0.201	8.470	<0.001
Rented from private landlord	0.242	0.225	1.300	0.193
Other	0.018	0.020	-0.340	0.731
Year (2012 is baseline)				
2013	0.174	0.217	-3.360	0.001
2014	0.210	0.183	2.260	0.024
2015	0.244	0.180	5.130	<0.001
2016	0.286	0.190	7.580	<0.001

Table C2. Comparisons of Means after Matching (Caliper Size of 0.001)

	After matching (caliper size of 0.001)			
Variables	**Treated**	**Control**	***t*-statistic**	***p*-value**
Independent variables				
Concern about saving energy	0.107	0.087	0.480	0.632
Concern about national energy	-0.022	-0.008	-0.330	0.745
Concern about climate change	0.014	0.040	-0.630	0.531
Control variables				
Concern about daily expenses	0.010	0.038	-0.660	0.512
Attitude toward renewables	0.046	0.057	-0.260	0.797
Age	3.338	3.233	1.500	0.134
Female	0.500	0.519	-0.890	0.374
Rural	0.174	0.180	-0.390	0.698
Household size	2.780	2.843	-1.120	0.262
Having a child	0.385	0.394	-0.430	0.664
Income reported	0.782	0.773	0.510	0.611
Income reported × Amount	1.751	1.722	0.460	0.645
Social class (A is baseline)				
Class B	0.134	0.133	0.060	0.950
Class C1	0.251	0.257	-0.290	0.770
Class C2	0.198	0.206	-0.420	0.673
Class D	0.177	0.167	0.620	0.537
Class E	0.217	0.219	-0.100	0.918
Housing tenure (being bought on mortgage is baseline)				
Owned outright by household	0.219	0.206	0.780	0.437
Rented from local authority	0.286	0.288	-0.090	0.925
Rented from private landlord	0.249	0.259	-0.540	0.592
Other	0.019	0.015	0.650	0.513
Year (2012 is baseline)				
2013	0.180	0.190	-0.600	0.549
2014	0.215	0.209	0.310	0.756
2015	0.239	0.227	0.650	0.515
2016	0.276	0.281	-0.240	0.813

Table C3. Comparisons of Means after Matching (Caliper Size of 0.0005)

	After matching (caliper size of 0.0005)			
Variables	**Treated**	**Control**	***t*-statistic**	***p*-value**
Independent variables				
Concern about saving energy	0.089	0.069	0.490	0.627
Concern about national energy	-0.021	0.003	-0.560	0.573
Concern about climate change	0.020	0.054	-0.790	0.431
Control variables				
Concern about daily expenses	-0.001	0.041	-0.950	0.343
Attitude toward renewables	0.038	0.068	-0.690	0.491
Age	3.364	3.260	1.440	0.151
Female	0.501	0.521	-0.900	0.366
Rural	0.174	0.184	-0.560	0.575
Household size	2.753	2.819	-1.180	0.239
Having a child	0.371	0.383	-0.580	0.564
Income reported	0.776	0.766	0.510	0.609
Income reported × Amount	1.756	1.734	0.340	0.736
Social class (A is baseline)				
Class B	0.136	0.136	0.000	1.000
Class C1	0.255	0.263	-0.440	0.659
Class C2	0.197	0.205	-0.430	0.668
Class D	0.181	0.160	1.260	0.208
Class E	0.208	0.216	-0.470	0.636
Housing tenure (being bought on mortgage is baseline)				
Owned outright by household	0.224	0.211	0.730	0.466
Rented from local authority	0.267	0.272	-0.290	0.771
Rented from private landlord	0.256	0.263	-0.390	0.695
Other	0.019	0.016	0.650	0.513
Year (2012 is baseline)				
2013	0.184	0.194	-0.610	0.545
2014	0.212	0.211	0.050	0.958
2015	0.237	0.226	0.610	0.541
2016	0.274	0.273	0.050	0.962

Table C4. Comparisons of Means after Matching (Caliper Size of 0.0001)

	After matching (caliper size of 0.0001)			
Variables	**Treated**	**Control**	***t*-statistic**	***p*-value**
Independent variables				
Concern about saving energy	0.041	0.028	0.290	0.775
Concern about national energy	0.005	0.041	-0.810	0.416
Concern about climate change	0.040	0.076	-0.790	0.428
Control variables				
Concern about daily expenses	-0.018	0.039	-1.240	0.215
Attitude toward renewables	0.065	0.074	-0.200	0.844
Age	3.481	3.366	1.470	0.141
Female	0.500	0.531	-1.330	0.183
Rural	0.171	0.188	-0.960	0.338
Household size	2.670	2.742	-1.200	0.229
Having a child	0.331	0.347	-0.730	0.467
Income reported	0.762	0.752	0.480	0.630
Income reported × Amount	1.777	1.738	0.540	0.587
Social class (A is baseline)				
Class B	0.146	0.147	-0.060	0.948
Class C1	0.269	0.271	-0.100	0.918
Class C2	0.197	0.199	-0.120	0.908
Class D	0.173	0.158	0.860	0.387
Class E	0.189	0.204	-0.810	0.418

Housing tenure (being bought on mortgage is baseline)				
Owned outright by household	0.243	0.226	0.870	0.386
Rented from local authority	0.229	0.234	-0.270	0.786
Rented from private landlord	0.261	0.270	-0.470	0.640
Other	0.018	0.016	0.360	0.722
Year (2012 is baseline)				
2013	0.194	0.212	-0.970	0.332
2014	0.217	0.203	0.790	0.430
2015	0.236	0.228	0.440	0.664
2016	0.248	0.249	-0.050	0.958

Results of Mahalanobis Distance Matching

Table C5. Matched Sample and Testing Results of H1-H4

Dependent variable	**Energy-saving behaviors**	
Specifications	**(1)**	**(2)**
Adoption and moderating effects		
SMT Adoption (H1)	0.142***	0.158***
	(0.0419)	(0.0426)
× Concern about Saving energy (H2)		-0.164***
		(0.0504)
× Concern about National Energy (H3)		0.0248
		(0.0503)
× Concern about Climate Change (H4)		0.0624
		(0.0524)
Household-specific Controls	Included	Included
Group-specific Year Fixed Effects	Included	Included
Observations	2,170	2,170
R-squared	0.155	0.161

Note: Robust standard errors are in parentheses. *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$. All estimates are adjusted by the matching weight, as one-to-one matching without replacement is not applicable in Mahalanobis distance matching. Group-specific year fixed effects indicate that each level of sex, age, social grade, region, or housing tenure has its own year fixed effects, resulting in 85 coefficients.

Table C6. Matched Sample and Testing Results of H5

Dependent variable	**Energy-saving behaviors**
SMT adoption and usage intensity	
SMT Adoption	-0.00589
	(0.0788)
× Monitoring at least occasionally (H5a)	0.221**
	(0.0896)
× Monitoring every day (H5b)	0.0256
	(0.0899)
Household-specific controls	Included
Group-specific year fixed effects	Included
Observations	1,315
R-squared	0.203

Note: Robust standard errors are in parentheses. *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$. All estimates are adjusted by the matching weight, as one-to-one matching without replacement is not applicable in Mahalanobis distance matching. Group-specific year fixed effects indicate that each level of sex, age, social grade, region, or housing tenure has its own year fixed effects, resulting in 85 coefficients. We exclude SMT adopters who did not adopt in-home displays (IHDs), given that they adopted alternative channels such as online webpages and television.

Appendix D: Procedures and Results of Placebo Tests

Details of Random Implementation Tests

We shuffled the 1,164 indicators of SMT adoption in our original sample to a randomly selected set of (new) observations within each year, thereby creating a placebo treatment. We then estimated Equation 1 and stored the coefficient of this placebo-treatment and replicated this procedure 1,000 times. For Equation 2, we shuffled the 683 adoption indicators in the same way. If the probability of randomly obtaining greater or equal absolute values of coefficients was not sufficiently small, we concluded that our estimates were likely to be obtained by chance.

Figure D1 presents the distributions of the estimated coefficients, and Table D1 summarizes the results. We found that the estimated average coefficients are indistinguishable from zero. Also, we calculated the *Z*-scores of our main estimates in Column 5 in Table 3 and Column 3 in Table 4 with regard to the coefficient distribution of the placebo treatments. We observed that the estimates are statistically significant at the 5% level only when their hypotheses were previously supported. Taken in sum, our findings were unlikely to be obtained by chance or outliers.

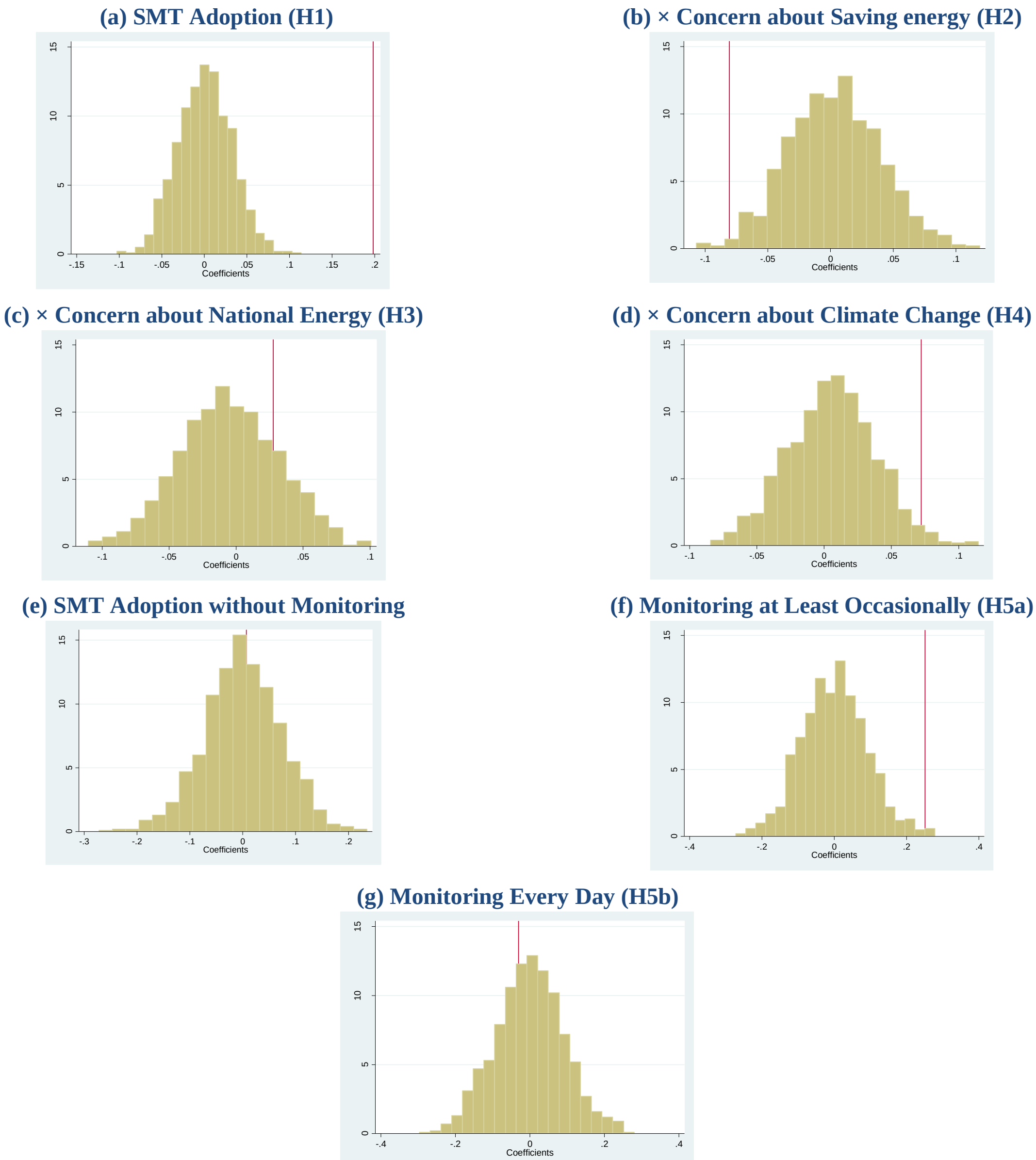

Figure D1. Random Implementation Testing Results

Table D1. Random Implementation Tests

Variables	Estimates	μ of Coeff.	σ of Coeff.	Z-score	*p*-value
SMT adoption and interactions					
SMT Adoption (H1)	0.1983	0.0005	0.0315	6.279	< 0.0001
× Concern about saving energy (H2)	-0.0806	0.0031	0.0366	-2.289	0.0221
× Concern about national energy (H3)	0.0277	-0.0053	0.0367	0.895	0.3708
× Concern about climate change (H4)	0.0721	0.0059	0.0326	2.034	0.0420
Moderating effects of usage intensity					
SMT adoption	0.0069	-0.0005	0.0725	0.102	0.9188
× Monitoring at least occasionally (H5a)	0.2512	0.0003	0.0905	2.772	0.0056
× Monitoring every day (H5b)	-0.0305	-0.0001	0.0920	-0.331	0.7406

Details of Placebo Effects of Solar Thermal Panel Adoption

As another placebo test, we utilized the adoption of solar thermal panels as a fake treatment. This pro-environmental technology could be associated with energy-saving motivations; however, it is unlikely to induce energy-saving behaviors as it does not provide useful information to change consumers' behaviors. If the fake treatment presents significant results, as shown from SMT adoption, we will conclude that our findings are driven by unobservable factors associated with the adoption of sustainable technologies instead of information gain from SMT adoption.

Our testing procedure is as follows. First, we operationalized solar thermal panel adoption in the following way. In the survey administered by the DECC, solar thermal panels are defined as "solar panels for hot water, not solar PV panels which generate electricity." With respect to installing solar thermal panels, respondents selected one of ten possible answers as follows:

1. Already done/have this
2. In the process of doing this
3. Thinking about doing this
4. Would like to do this, but not at this stage
5. Don't want to/won't do this
6. Haven't thought about doing this
7. Haven't heard of this
8. Not my decision to make because I'm renting the property
9. Not possible to install in my property
10. Don't know

Among these answers, we excluded households who chose either (8), (9) or (10) since they were not in control of their facilities or not aware of whether solar thermal panels were installed. Note that "Don't know" is taken to indicate that a respondent has heard of solar thermal panels before. In our analysis, adoption is defined as 1 if a household selected either (1) or (2), and 0 otherwise. In our data, 140 households (2.04%) adopted solar thermal panels.

By replacing smart meter adoption with solar thermal panel adoption in Equation 1, we tested the placebo effect (see Table D2). We found that solar panel adoption is not significantly associated with energy-saving behaviors. We also found that the interaction terms between the adoption and energy-saving motivations are not significant. Moreover, we observed positive and significant coefficients of SMT adoption after controlling for the adoption of solar thermal panels (Columns 3 and 4). These results indicate that the positive relationship between SMT adoption and energy-saving behaviors is unlikely to be driven by unobservable factors such as potential reporting bias and measurement errors of energy-saving attitudes.

Table D2. Placebo Effects of Solar Thermal Panel Adoption on Energy-Saving Behaviors

Dependent variables	**Energy-saving behaviors**			
Models	**(1)**	**(2)**	**(3)**	**(4)**
Independent variables				
Concern about saving energy	0.275***	0.274***	0.269***	0.269***
	(0.0132)	(0.0133)	(0.0132)	(0.0133)
Concern about national energy	0.0505***	0.0477***	0.0493***	0.0467***
	(0.0136)	(0.0138)	(0.0136)	(0.0138)
Concern about climate change	0.0656***	0.0683***	0.0663***	0.0688***
	(0.0129)	(0.0131)	(0.0129)	(0.0130)

Adoption and Interactions				
SMT Adoption			0.190***	0.188***
			(0.0339)	(0.0340)
Solar thermal panel adoption	0.0670	0.0440	0.0552	0.0315
	(0.0784)	(0.0906)	(0.0773)	(0.0895)
× Concern about saving energy		0.0416		0.0418
		(0.102)		(0.101)
× Concern about national energy		0.123		0.117
		(0.0798)		(0.0784)
× Concern about climate change		-0.106		-0.0961
		(0.0772)		(0.0765)
Household-specific controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	6,857	6,857	6,857	6,857
R-squared	0.124	0.124	0.128	0.128

Note: Robust standard errors are in parentheses. *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$. We exclude households who were not in control of their facilities or not aware of whether solar thermal panels were installed.

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