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Prices, information and nudges for residential electricity conservation: A meta-analysis *

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Abstract

Incentivising households to lower their electricity consumption is increasingly used as a tool to create a more flexible electricity demand. Previous reviews estimate that electricity savings of 6.4-7.4% can be achieved through monetary, informational and behavioural incentives. This paper argues that a more realistic estimate is of a 1.9-3.9% reduction in consumption based on the most recent experimental data, from both peer-reviewed and grey literature sources. Using data from 52 studies published during the "Smart Grid Era" (2005 onwards), the effects of incentives from 128 observations, amounting to 713 002 households, are analysed. The results show that individual and real-time feedback as well as personalised advice on how to save electricity are more effective than feedback on electricity costs and general electricity savings tips which lead to relative increases in consumption. Despite improvements in the quality of more recent studies, the analysis highlights the importance of methodological rigour in carrying out and reporting effects of incentives: an absence of a control group, of socio-demographic data, and the self-selection of participants into treatment leads to overestimation of effects.

Keywords: electricity consumption, electricity conservation, feedback, incentives, meta-analysis, nudges, pricing, residential

1. Introduction

Across the globe, countries are committing to increasing the share of production from renewable energy sources (RES) (United Nations, 2017). This

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4 transition is facilitated by the upgrading of the grid to a smarter, more efficient,
5 more reliable network in which RES can be more easily integrated (Gungor *et al.*,
6 2011). The movement from a fossil fuel dependent energy system to one based
7 on production from RES requires a re-imagining of the way in which residen-
8 tial consumers interact with the electricity grid. Rather than supply following
9 demand, as is the traditional operation of electricity markets, the intermittent
10 nature of production from RES calls for a greater level of flexibility in demand.

11 Previous demand reduction strategies have focused on increasing energy effi-
12 ciency³ as a way to lower consumption. However, despite a 33% increase in
13 energy efficiency (European Environment Agency, 2016), residential energy con-
14 sumption in the EU increased by 9% between 1990 and 2013⁴. The increase in
15 consumption can be associated to the rebound effect and the focus on energy
16 efficiency as end rather than a means to achieving energy demand reduction
17 (Maréchal and Holzemer, 2015).

18 Another demand reduction strategy focuses on ways to incentivise residential
19 consumers to modify their electricity consuming behaviour. The installation of
20 smart meters as part of the wider smart grid infrastructure, provides two-way
21 communication between the household and the energy company, and allows
22 residential consumers to take a more active role in the management of their
23 electricity consumption. In the traditional electricity market, the residential
24 consumer is a passive user for whom electricity is invisible and readily available
25 (Darby *et al.*, 2006; Burgess and Nye, 2008; Hargreaves *et al.*, 2010). In the
26 new market, the residential electricity consumer is better informed and more
27 conscious of how much they consume. With technological improvements to
28 the grid underway, consumers can receive appropriate incentives to lower their
29 electricity consumption.

30 The incentives tested in pilot studies and field experiments fall into three
31 principal categories: monetary, informational and behavioural incentives. Mon-
32 etary incentives include information on monetary expenditure on electricity, and
33 pricing strategies. Such incentives allow households to better connect their con-
34 sumption with its costs and encourage them to modify their behaviour to lower
35 their costs. In the case of pricing strategies such as dynamic pricing, increasing
36 the cost of electricity should, according to standard economic theory, incentivise
37 households to consume less.

38 Non-monetary incentives can be further categorised into personal feedback
39 on consumption, and social feedback. Personal feedback refers to information
40 on a household's own consumption whether via a traditional paper bill, or in
41 real-time with an in-home display⁵. Personal feedback also includes advice on

³Such energy efficiency measures include the installation of home insulation, and the up-
grading of old appliances to more energy efficient appliances, among others.

⁴In 2014, the European Environment Agency (2017) report the first decrease in total
household energy consumption since 1990 of 4%. In all previous years, household energy
consumption has increased compared to 1990 levels, peaking in 2010.

⁵An in-home display (IHD) is an electronic device which provides a household with real-
time feedback on their energy consumption.

42 how to reduce electricity consumption, whether this is general advice or advice
43 tailored to a particular household. By providing consumers with electricity
44 consumption information and informing them of the consequences of increased
45 consumption, rational consumers will make the decision to lower their electricity
46 demand (Frederiks *et al.*, 2015). In reality, individuals do not behave rationally
47 and so providing a greater level of information and monetary incentives may
48 not be sufficient to encourage all consumers to modify their behaviour.

49 Social feedback refers to comparisons of a household’s consumption with
50 that of other households. Such incentives are based on behavioural economic
51 and psychological theories which show that individuals use heuristics, or rules-
52 of-thumb, to simplify complex decision making (Samson *et al.*, 2018). In the
53 current context, households are informed of their consumption compared to the
54 average consumption of their neighbours and receive social approval of their
55 behaviour when they consume less than their neighbours via the use of positive
56 reinforcement (Schultz *et al.*, 2007).

57 This paper uses a meta-analytical approach to explore feedback in field ex-
58 periments and pilot studies in order to evaluate the effect of different incentives
59 on households’ electricity consumption behaviour. The objective is to combine
60 the results of many studies to provide a better estimate of the true effect of the
61 different incentive types on residential electricity consumption. The questions
62 posed in this paper are: Which incentives are most effective at encouraging
63 households to lower their electricity consumption? How does the design of the
64 experimental study impact the effectiveness of different incentives?

65 The current meta-analysis adds to literature on meta-analyses which explore
66 incentives for reducing household electricity consumption by including recent
67 studies, those published from 2005 up to 2019 (the time of data collection). By
68 focusing on this time period, named the ”Smart Grid Era” by McKerracher and
69 Torriti (2013), a more accurate estimate of the effect of an incentive on current
70 electricity consumption is calculated. Additionally, the present analysis includes
71 studies from both peer reviewed literature and utility and government reports
72 in order to have as varied a database of studies as possible as the objectives
73 of those carrying out the experiments are not necessarily the same. Academic
74 researchers have a final objective to publish their research, whereas those work-
75 ing for utilities and governments seek to determine the return on investment
76 in incentives. It can be argued that experiments with larger sample sizes pro-
77 vide more robust results, often utilities have the means to run large trials of
78 different incentives. Finally, if only peer reviewed articles are taken into con-
79 sideration, there may be an issue of bias in the selection of studies used for the
80 meta-analysis. The issue of publication bias is assessed in this paper.

81 Compared to previous meta-analyses, a finer level of detail regarding the dif-
82 ferent incentives is used. In particular, the incentives regarding social feedback
83 are separated into those which provide descriptive comparative feedback alone
84 and those which also include approval or disapproval of behaviour as the former
85 has been shown to result in a boomerang effect where households who consume
86 less than their neighbours increase their consumption (Schultz *et al.*, 2007).
87 Furthermore, a greater level of study design variables, such as how households

88 are recruited into the study, and how they are assigned to the treatment groups
89 is included. Studies which recruit participants on an opt-in basis and do not
90 randomise assignment to treatment groups may be subject to selection bias as
91 those households who have favourable consumption patterns or are predisposed
92 to lower electricity consumption are more likely to take part (Alexander, 2010;
93 Ericson, 2011; Buchanan *et al.*, 2015). The final added-value of the present
94 meta-analysis is the inclusion of external factors which can influence energy
95 consumption: a country’s climate and energy consumption level.

96 The following section describes the different incentives used in the exper-
97 imental literature and sets out the hypotheses which will be tested. This is
98 followed by a discussion of previous meta-analyses and reviews in Section 3.
99 Section 4 describes the data collection method, the model used and the vari-
100 ables of interest. Section 5 presents the results, Section 6 discusses the results
101 and finally, Section 7 concludes.

102 **2. Incentives for lowering residential electricity consumption**

103 Electricity is characterised as an invisible and abstract force that arrives in
104 households via hidden wires (Burgess and Nye, 2008; Hargreaves *et al.*, 2010).
105 Unlike other goods, it is consumed indirectly as an input into individuals’ daily
106 activities and routines (Gillingham *et al.*, 2009). Furthermore, electricity con-
107 suming activities are not made solely at the individual level, they are also made
108 at the household level (Bird and Legault, 2018), thus complicating efforts to
109 lower consumption.

110 The principal strategies employed in the experimental literature to incen-
111 tivise households to reduce their consumption are separated, in the present
112 analysis, into monetary, informational and behavioural incentives. Each cat-
113 egory evokes different motives to save electricity and works through different
114 mechanisms as will be discussed in this section.

115 *2.1. Monetary incentives*

116 This category includes pricing strategies which provide direct monetary in-
117 centives to lower consumption, through rewards for achieving savings, rebates
118 and increasing prices, and monetary information which acts indirectly on mon-
119 etary incentives by triggering cost saving motivations (Fischer, 2008).

120 Any reduction in electricity consumption leads to financial benefits for house-
121 holds and financial motives are typically cited by households as the main rea-
122 son for choosing to take part in experimental studies (Hargreaves *et al.*, 2010;
123 Goulden *et al.*, 2014). So long as the financial benefits of reducing electricity
124 consumption outweigh the costs, households are expected to make efforts to
125 lower their consumption.

126 Varying prices provide consumers with economic incentives to reduce (in-
127 crease) their electricity consumption during peak (off-peak) periods by better
128 aligning the retail price of electricity with the wholesale price in order to main-
129 tain supply and demand balance in the electricity market (Borenstein *et al.*,

130 2002). Under expected utility theory, a rational individual will lower their
131 consumption when faced with an increased price or the possibility of a mon-
132 etary reward for doing so. Such pricing tariffs are seen to be effective at re-
133 ducing demand during periods of high demand but less effective at reducing
134 overall demand (Allcott, 2011b). In particular, households may increase over-
135 all consumption if they are incentivised to increase off-peak consumption by
136 an amount greater than they are incentivised to decrease peak consumption
137 (Torriti, 2012). Yet, these strategies can have spillover effects when behaviour
138 to reduce consumption during a peak period carries over into off-peak periods
139 (Allcott, 2011a).

140 By providing households with information on how much their electricity
141 consumption costs (as opposed to information on the amount of electricity con-
142 sumed), households can see the monetary benefits of reducing their electricity
143 consumption. In interviews with households participating in electricity conser-
144 vation field experiments, residents preferred to receive feedback in monetary
145 terms as this is considered to be more relatable, and more comparable, than
146 electricity units (Hargreaves *et al.*, 2010; Raw and Ross, 2011).

147 On the other hand, monetary incentives may crowd out an individual’s exist-
148 ing intrinsic motivation to reduce their consumption due to pro-social or altru-
149 stic motives (Bowles, 2008; Smith *et al.*, 2012). In particular, interviews with
150 households have revealed that the possible monetary savings are often negligible
151 (Hargreaves *et al.*, 2010; Goulden *et al.*, 2014).

152 *2.2. Informational incentives*

153 Information on electricity consumption can be provided through individual
154 feedback on a household’s current and historic electricity consumption. It can be
155 received through detailed electricity bills (see Carroll *et al.*, 2014; Schleich *et al.*,
156 2013), online via a website (see Benders *et al.*, 2006; Ueno *et al.*, 2006; Glerup
157 *et al.*, 2010; Vassileva *et al.*, 2012; Mizobuchi and Takeuchi, 2013; Schleich *et al.*,
158 2013; Harries *et al.*, 2013; Houde *et al.*, 2013), or in real-time via a monitor in
159 the home (see Van Dam *et al.*, 2010; Grønhoj and Thøgersen, 2011; Alahmad
160 *et al.*, 2012; Carroll *et al.*, 2014; Schultz *et al.*, 2015).

161 Feedback on consumption increases households’ awareness of their consump-
162 tion thus reducing the invisible quality of electricity supply. By increasing the
163 saliency and relevance of consumption, individual feedback highlights how much
164 electricity different activities consume (Fischer, 2008; Buchanan *et al.*, 2014). If
165 the feedback shows a discrepancy in an individual’s perception of normal con-
166 sumption, then control theory suggests that the individual enters a “negative
167 feedback loop” in which they adapt their behaviour to change future feedback,
168 or change their perception of normal consumption, or they withdraw from the
169 situation (Kluger and DeNisi, 1996). Concerning the latter, interviewed house-
170 holds have reported moving in-home displays (IHDs) to cupboards to avoid
171 being reminded of their consumption (Hargreaves *et al.*, 2013).

172 According to the theory of norm activation, feedback affects individual be-
173 haviour by allowing individuals to identify a problem, to realise that their be-
174 haviour influences the identified problem, and finally, to become aware of how

175 their behaviour affects the problem (Fischer, 2008). Feedback improves aware-
176 ness of the link between households' actions and their electricity consumption,
177 thus improving the "action-effect relationship" (Fischer, 2008; Abrahamse and
178 Steg, 2009). Furthermore, the sooner feedback is received after the occurrence
179 of a particular action, the greater the influence on behaviour (Darby *et al.*, 2006;
180 Dwyer *et al.*, 2015).

181 While feedback directs households' attention to their electricity consump-
182 tion, it can lack context. Households learn of how much they consume but in
183 the absence of a desire to reduce their consumption or of the knowledge of how
184 to do so, behavioural changes may not be made (McCalley and Midden, 2002;
185 Abrahamse *et al.*, 2005). The knowledge of how to achieve a certain outcome,
186 or procedural knowledge, can lead to individuals providing conservation efforts
187 (De Young, 2000).

188 In order to assess the effect of providing households with the knowledge
189 of how to reduce their electricity consumption, two further types of informa-
190 tional incentives are evaluated. Households can receive advice tailored to their
191 particular situation (both house and household characteristics) (Allcott, 2011b;
192 Ayres *et al.*, 2012; Costa and Kahn, 2013) or more general electricity savings
193 tips (Ueno *et al.*, 2006; Mountain, 2008; Van Dam *et al.*, 2010; Raw and Ross,
194 2011).

195 These informational incentives work by providing households with actions
196 that they can take to reduce their consumption. When the information is tai-
197 lored to a household's particular situation, the actions are more relevant. Such
198 approaches are more particularistic and their effectiveness is dependent on the
199 provider of the advice (De Young, 2000). On the other hand, such information
200 may have a detrimental effect by overloading individuals with actions and tips
201 that they are more than likely already aware of (Fischer, 2008). Indeed, the
202 provision of ways to conserve electricity may result in psychological reactance
203 where an individual feels their liberty to do as they wish is restricted and so
204 they display the undesirable behaviour (Brehm, 1966; De Young, 2000).

205 *2.3. Behavioural incentives*

206 Behavioural incentives, also coined as nudges, encourage a certain behaviour
207 by acting upon systematic biases in individuals' decision making. They do not
208 affect economic incentives and nor do they provide information alone (Thaler
209 and Sunstein, 2008).

210 In the electricity conservation literature, households are informed of others'
211 electricity consumption, such as neighbours' or similar households', in relation
212 to their own. This comparative feedback is an intervention which has been in-
213 creasingly explored in recent experimental studies and uses the notions of social
214 and injunctive norms. According to the focus theory of normative conduct, a
215 social norm refers to descriptive consumption feedback of personal consump-
216 tion compared to that of other households, whereas an injunctive norm also
217 reinforces whether a particular behaviour is socially approved or disapproved
218 of (Cialdini *et al.*, 1991). In the case of electricity consumption, an injunctive

219 norm confirms whether a household’s consumption is pro-social, i.e. whether
220 the household is a low-consuming household (Schultz *et al.*, 2007).

221 These two types of behavioural incentive have been separated in the present
222 analysis as there is evidence that solely descriptive comparative feedback (social
223 norms) leads to a boomerang effect where low-consuming households increase
224 their consumption, converging towards the average (Schultz *et al.*, 2007; Allcott,
225 2011b; Ayres *et al.*, 2012). Low-consuming households may increase their con-
226 sumption in order to conform to the norm (Fischer, 2008) or because they feel
227 ‘licensed’ to increase their consumption after previous virtuous efforts to lower
228 it (Khan and Dhar, 2006). The inclusion of injunctive norms reinforces the
229 idea that households who consume less than average are engaged in pro-social
230 behaviour and so they do not increase their consumption (Cialdini *et al.*, 1990).
231 According to Miller and Prentice (2016) a social norm is better used for under-
232 performing individuals (over-consumers) as such individuals are concerned with
233 social status and an injunctive norm for over-performing individuals (under-
234 consumers) to positively frame their behaviour and to “leverage their concern
235 for normative correctness” (Farrow *et al.*, 2017).

236 Such methods of feedback may be successful by creating competition within
237 a neighbourhood, or by highlighting the social cost of electricity consump-
238 tion. Concerning the former, the group to which households are compared is of
239 paramount importance; the comparison group must be relevant to the identity
240 of the particular households (Farrow *et al.*, 2017). Furthermore, comparative
241 feedback may create a situation of conditional cooperation where households
242 consume more (less) after learning that others are consuming more (less)⁶ (All-
243 cott, 2011b; Farrow *et al.*, 2017; Bird and Legault, 2018).

244
245 The above discussion of the economics and psychological literature on incen-
246 tives to lower electricity consumption leads to the formulation of the following
247 hypotheses:

248 H1 Monetary incentives including *pricing strategies* and *monetary informa-*
249 *tion* reduce residential electricity consumption.

250 H2 Informational incentives including *individual* and *real-time feedback*, *per-*
251 *sonalised advice* and *saving tips* reduce residential electricity consumption.

252 H3 Behavioural incentives including *social norms* and *injunctive norms* re-
253 *duce* residential electricity consumption.

254 3. Previous Meta-Analyses

255 The effect of different feedback types and monetary incentives on electricity
256 consumption has been studied by researchers and utilities alike since the 1970s,

⁶Such behaviour is often observed in public goods (Fischbacher *et al.*, 2001; Frey and Meier, 2004) and common pool resource games (Ostrom, 1990; Velez *et al.*, 2009).

Authors	Objective	Time-frame	Studies	Effect sizes
Darby (2006)	Effect of direct and indirect feedback on energy (gas and electricity)	1979-2006	38	Direct: -15% to -5%; Indirect: -10% to 0%
Ehrhardt-Martinez et al. (2010)	Effect of different feedback treatments on energy consumption	1974-2010	57	-12% to -4%
Faruqui et al. (2010)	Effect on IHDs on energy consumption	1989-2010	12	-13% to -3%
Delmas et al. (2013)	Reduction in energy consumption via different treatments	1975-2012	59	-55% to +18%; ATE ⁷ : -7.4%
McKerracher and Torriti (2013)	Effect of IHDs on energy consumption	1979-2015	27	-5% to -3%; ATE: -6.4%
Andor and Fels (2018)	Effect of behavioural interventions on energy consumption	1978-2017	44	-1.2% to 30%
Bird and Legault (2018) ⁸	Efficiency of information and behavioural interventions	1978-2018	-	-

Table 1: Summary of results of previous reviews and meta-analyses

257 and as such, several reviews and analyses have been undertaken (see Darby
258 *et al.*, 2006; Ehrhardt-Martinez *et al.*, 2010; Faruqui *et al.*, 2010; Delmas *et al.*,
259 2013; Faruqui and Sergici, 2013; McKerracher and Torriti, 2013; Andor and Fels,
260 2018; Bird and Legault, 2018). Table 1 summarises the results of the previous
261 reviews and analyses discussed in this section.

262 Darby *et al.* (2006) review 38 feedback studies from 1979 to 2006 and con-
263 clude that, on average, direct feedback which is received immediately after the
264 electricity consuming behaviour is more effective than indirect feedback such as
265 a paper bill. Both Faruqui *et al.* (2010) and McKerracher and Torriti (2013)
266 analyse the effect of real-time feedback, via an IHD, on electricity consump-
267 tion. In a review of 12 pilot studies (1989-2010), Faruqui *et al.* (2010) find an
268 energy reduction of 18% on average. McKerracher and Torriti (2013) perform
269 a wider analysis of 27 peer and non peer reviewed studies between 1979-2011.
270 The authors find that as sample size increases, the reported treatment effect
271 decreases. Additionally, they classify studies via sampling selection and recruit-
272 ment method and find that studies with more representative samples report
273 lower percentages of energy reduction.

274 Ehrhardt-Martinez *et al.* (2010) review 57 studies from 1974-2010 covering
275 both feedback and dynamic pricing studies using advanced metering infras-
276 tructure. The authors conclude that feedback interventions result in a greater
277 overall reduction in electricity consumption than dynamic pricing which is more
278 effective at decreasing demand at peak times.

279 Delmas *et al.* (2013) analyse 59 studies from 1975 to 2012 finding that per-
280 sonalised advice (energy audits and consulting) and real-time feedback are most
281 effective at reducing energy consumption. The authors compare the average
282 treatment effects of studies of higher quality (those which include a control

⁷Average Treatment Effect.

⁸The number of studies and effect sizes are not given for Bird and Legault (2018) as they provide a qualitative review of a non-specified number of studies.

283 group, and control for demographic information and for weather changes) to
284 lower quality studies with fewer controls. They find that higher quality studies
285 report a lower reduction in energy consumption (Delmas *et al.*, 2013).

286 Andor and Fels (2018) systematically review 44 studies from 1978 to 2017,
287 focusing on behavioural interventions; social comparisons, commitment devices,
288 goal setting and labelling⁹. The authors conclude that social comparison studies
289 are the most effective at reducing energy consumption compared to commitment
290 devices and goal setting. However, they are also the most researched at present
291 and the studies are often of better quality. By quality, the authors refer to the
292 use of randomised controlled trials with large, representative samples, and to
293 methodological rigour in reporting results.

294 Bird and Legault (2018) perform a qualitative review of energy conservation
295 studies from 1978 to 2018 focussing on information feedback and behavioural
296 interventions. In particular, they highlight the need for further studies into
297 the persistence of interventions and ways in which to effectively target low-
298 consuming individuals. They also call for greater methodological rigour in the
299 design and implementation of field experiments.

300 These reviews and analyses have covered studies across a long time period,
301 from the seventies and eighties to the present. Ehrhardt-Martinez *et al.* (2010)
302 find trends in energy savings across two distinct periods; the *Energy Crisis*
303 *Era* from the seventies to 1995, and the *Climate Change Era* from 1995 to
304 2010. McKerracher and Torriti (2013) identify an additional era, from 2005
305 onwards which they name the *Smart Grid Era*. The current paper seeks to bet-
306 ter understand the effect of different interventions on electricity consumption
307 by considering solely studies from 2005 onwards so as to focus on the Smart
308 Grid Era. As Ehrhardt-Martinez *et al.* (2010, p.74) note, “studies that compare
309 feedback-related savings across all four decades may result in inflated expecta-
310 tions regarding potential energy savings today”.

311 The discussion of previous reviews and analyses leads to the formulation of
312 three additional hypotheses:

313 H4 As *sample size* increases, smaller effects of incentives on electricity con-
314 sumption are observed.

315 H5 Studies with *more controls* (inclusion of control group, weather controls,
316 demographic controls, opt-out recruitment, random assignment to treat-
317 ment group) show a smaller reduction in electricity consumption.

318 H6 Average effect of incentives on electricity consumption is lower in *Smart*
319 *Grid Era* compared to previous eras.

⁹The labelling intervention is applied to the purchase of energy efficient appliances rather than to energy conservation efforts.

320 **4. Method**

321 *4.1. Data Collection*

322 In order to find appropriate articles for this analysis, the following databases
323 were searched in November 2019 for articles written in English and carried out
324 in developed countries: CrossRef, EconLit, EconPapers Repec, Google Scholar,
325 NBER, ScienceDirect, SpringerLink, Web of Science, SSRN for the following
326 sets of keywords using Boolean logic:

- 327 • Keywords concerning type of consumption: electricity consumption, elec-
328 tricity demand, electricity usage, energy consumption, energy demand,
329 energy usage, and;
- 330 • Keywords concerning the type of incentive:
 - 331 – Incentive, behaviour
 - 332 – Informational feedback: smart meter, advanced met*, feedback, nudge,
333 norm,
 - 334 – Financial feedback: dynamic pricing, tariff, time of use, critical peak
335 pricing, real time pricing, peak time rebate, and;
- 336 • Keywords concerning the level of consumption: residential, household,
337 consumer, and;
- 338 • Keywords concerning the study type: pilot, trial, experiment, field.

339 Across all databases, the search terms resulted in a list of 2 564 studies.
340 After eliminating doubles and assessing the titles of each study, 331 studies
341 were retained for screening. The screening of studies involved first, reading
342 each abstract (199 studies were eliminated at this stage) and second, reading
343 the entire paper (76 studies were excluded after a full assessment). In addition,
344 the reference lists and the lists of citing articles for each article selected for
345 full assessment, as well as previous meta-analyses, were scanned for further
346 relevant studies. The final sample includes 52 studies on the topic of using
347 incentives to reduce residential electricity consumption, of which 34 are from
348 the peer reviewed literature and 18 from the grey literature¹⁰. Figure 1 displays
349 a methodological flowchart of the process from initial data collection to the final
350 selection of studies.

351 The final list of articles, those in which the treatment effect is reported as the
352 change in electricity consumption of treated households compared to a baseline
353 or control group are reported in Table 2 and details on why 80 papers were
354 excluded can be found in Figure 1. A coding protocol was implemented for the
355 final selection of 52 studies which involved an experimentation of an incentive.

¹⁰Grey literature is defined as all studies which do not go through a peer review process as for published scientific articles. This includes utility and government reports, conference proceedings and working papers.

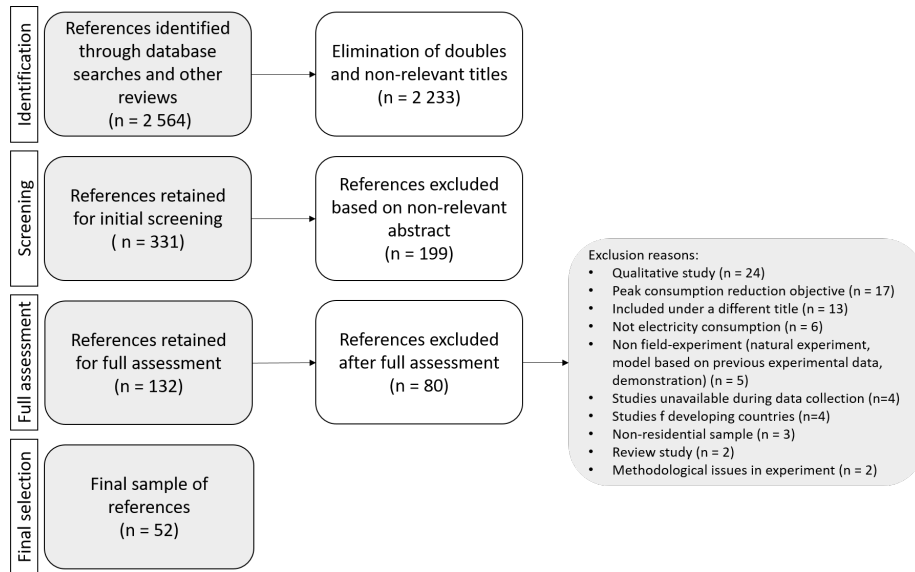


Figure 1: Flowchart of study selection methodology

356 The majority of articles came from economics, business, and energy journals.
 357 The reports are from utility and government websites as well as from consulting
 358 companies.

Author	Year	Publication Information
Alahmad et al.	2012	IEEE Transactions on Industrial Electronics
Allcott	2011	Resource and Energy Economics
Allcott	2011	Journal of Public Economics
Ayres et al.	2013	Journal of Law, Economics and Organization
Bager and Mundaca	2017	Energy Research & Social Science
Bariss et al.	2014	Energy Procedia
Bartusch et al.	2011	Energy Policy
Benders et al.	2006	Energy Policy
Bradley et al.	2016	Energy Policy
Carroll et al.	2014	Energy Economics
Costa and Kahn	2013	Journal of the European Economic Association
DECC	2015	Department of Energy & Climate Change
DNV KEMA	2014	DNV KEMA Energy and Sustainability
Dougherty	2013	Opinion Dynamics Corporation
D'Oca et al.	2014	Energy Research and Social Science
Faruqui and Sergici	2011	Journal of Regulatory Economics
Gleerup et al.	2010	Energy Journal
Grønhøj and Thøgersen	2011	International Journal of Consumer Studies
Harries et al.	2013	European Journal of Marketing
Henry et al.	2019	Energy Policy
Houde et al.	2013	Energy Journal
Iwafune et al.	2017	Energy

Table 2: Studies included in the meta-analysis

Author	Year	Publication Information
Kazukauskas et al.	2017	SSRN
Kendel and Lazaric	2015	Journal of Strategy and Management
Lynham et al.	2016	Energy Economics
Martin and Rivers	2015	(working paper)
Mizobuchi and Takeuchi	2013	Energy Policy
Mountain	2006	Hydro One Network Inc.
Mountain	2008	Hydro One Networks Inc.
Mountain	2012	Research Institute for Quantitative Studies
Mukai et al.	2016	Energy Efficiency
Nguyen et al.	2016	Energies
Nilsson et al.	2014	Applied Energy
Nilsson et al.	2018	Energy Policy
Parker et al.	2008	Florida Solar Energy Center
Provencher et al.	2015	Navigant
Raw and Ross	2011	Energy Demand Research Project:
Schleich et al.	2013	Energy Policy
Schultz et al.	2007	Psychological Science
Schultz et al.	2015	Energy
Shen et al.	2016	Energy Policy
Skumatz and Dimetrosky	2014	NMR Group Inc and Tetra Tech
Stinson et al.	2015	Energy Procedia
Sullivan et al.	2013	Freeman, Sullivan & Co.
Sullivan et al.	2016	Nexant
Torriti	2012	Energy
Ueno et al.	2005	European Council for an Energy Efficient Economy
Ueno et al.	2006	Applied Energy
Van Dam et al.	2010	Building Research and Information
Van Elburg	2014	Dutch Energy Savings Monitor
Vande Moere et al.	2011	IFIP Conference on Human-Computer Interaction
Vassileva et al.	2012	Applied Energy

Table 2: Studies included in the meta-analysis

359 Figure 2 displays the geographical distribution of included studies. The
360 majority of studies come from the United Kingdom and North America as these
361 countries have been at the forefront of field experiments and pilot studies on
362 incentives to reduce electricity consumption. In addition, this could also be
363 explained by the fact that one of the inclusion criteria is that the paper be
364 written in English and that experiments carried out by national utilities and
365 governments are likely to be written in the native language. This restriction
366 could result in publication bias which will be assessed below. Compared to
367 previous meta-analyses, there is an increasing number of studies from other
368 European countries (in particular the Netherlands and Sweden), and from Asian
369 countries (particularly Japan).

370 4.2. Model and Estimation Method

371 Meta-regression analysis is a quantitative method of systematically analysing
372 the results of empirical studies with a common objective. It goes beyond a
373 literature review as it allows the analyst to calculate a mean treatment effect
374 across studies by discovering which variables lead to differences in experiments



Figure 2: Geographical distribution of included studies

375 which study the same treatment effect (Stanley and Jarrell, 1989; Nelson and
 376 Kennedy, 2009). Meta-analyses are used to estimate a more precise estimate of
 377 the true effect of a treatment than any single study can do alone (Borenstein
 378 *et al.*, 2009).

379 Using notation from Stanley and Jarrell (1989), the following meta-regression
 380 model is estimated:

$$b_j = \beta + \sum_{k=1}^K \alpha_k Z_{jk} + e_j \quad \text{where } j = 1, \dots, L \quad (1)$$

381 where b_j is the effect size (percentage change in electricity consumption)
 382 reported in the j th primary study and β is the ‘true’ value of the effect being
 383 estimated. α_k are the meta-regression coefficients to be estimated which ex-
 384 press the biasing effect of the K meta-independent variables (typically dummy
 385 or indicator variable representing incentives, study design characteristics and
 386 external factors) represented by Z_{jk} . A positive value of α_k indicates a positive
 387 bias or an increase in electricity consumption and a negative value, a nega-
 388 tive bias or a decrease in consumption. Finally, e_j is the normally distributed
 389 sampling-estimation error with zero mean and variance σ_j^2 .

390 This model can be estimated by Ordinary Least Squares (OLS). However,
 391 given that in the sample of primary studies, there are effect sizes from studies of
 392 varied sample sizes, heteroscedasticity is an issue and the method of estimation
 393 by OLS may lead to inefficient and biased estimates. This bias can be mitigated
 394 by using White or Huber-White robust standard errors (Sebri, 2014), but the
 395 preferred approach is to weight equation 1 by an error of precision, the standard
 396 error of the effect size, to give more weight to more precise estimates (Stanley
 397 and Doucouliagos, 2012):

$$t_j = \frac{b_j}{S_{bj}} = \frac{\beta}{S_{bj}} + \sum_{k=1}^K \alpha_k \frac{Z_{jk}}{S_{bj}} + \frac{u_j}{S_{bj}} \quad \text{where } j = 1, \dots, L \quad (2)$$

398 In the primary studies collected for the present analysis, standard errors
399 are not always reported nor can they be constructed, thus a common approach
400 in meta-analysis is to proxy precision with a monotonic transformation of the
401 sample size of the primary observation (Nelson and Kennedy, 2009; Stanley and
402 Doucouliagos, 2012). As such, the square root of the sample sizes in the primary
403 studies are used as weights for the estimation following Delmas *et al.* (2013);
404 Sebri (2014); Van Houtven *et al.* (2017) such that experiments with a larger
405 sample are given more weight. Experiments with larger samples are considered
406 to be more representative of the population and so the estimated effect is a
407 better estimate of the ‘true’ effect.

408 In addition to heteroscedasticity, the present data may also suffer from issues
409 of publication bias, heterogeneity, and non-independence. Firstly, to limit
410 issues of publication bias, both peer reviewed articles and reports from the grey
411 literature are included in this analysis. In addition, after a description of the
412 dataset and before any models are estimated, the selection of primary studies
413 used in the meta-analysis is assessed for publication bias. This analysis leads
414 to the conclusion that publication bias is present up to a factor of 2 and that
415 using the sample size as a weight mitigates this problem (see Section 5.3).

416 Secondly, to tackle the sources of heterogeneity, a set of binary variables
417 describing the study characteristics which are potential sources of heterogeneity
418 are included in the regression (Section 4.3 describes the variables used in the
419 analysis), the temporal context has been limited to primary studies published
420 since 2005 representing the *Smart-Grid Era* (McKerracher and Torriti, 2013)
421 and only studies from developed countries are included.

422 Finally, to address the non-independence of several treatment effects coming
423 from the same primary study, the estimated standard errors are clustered by
424 primary study.

425 4.3. Variables

426 4.3.1. Dependent Variable

427 The variable of interest is the treatment effect reported in primary studies
428 as the percentage change in electricity consumption as a result of the imple-
429 mentation of an incentive. When a control group is present in an experiment,
430 the percentage change relative to the control group is used. If no control group
431 is present, the percentage change relative to the baseline is used¹¹. A negative
432 (positive) percentage indicates a reduction (increase) in electricity consumption.

433 4.3.2. Independent Variables

434 The independent variables refer to the type of intervention tested in the
435 primary study and the controls used. There are *pricing strategies*: households
436 receive a financial reward which is directly linked to their electricity conservation
437 effort or *monetary information*: participating households are given feedback on
438 how much their electricity consumption costs.

¹¹Presence of a control group is controlled for in the analysis to come.

439 *Individual feedback* refers to interventions where participants receive infor-
440 mation on their current and previous consumption in electricity units. This
441 refers to consumption information that is in addition to the standard electric-
442 ity bill, be it a more detailed bill, or consumption information on a web site.
443 *Real-time feedback* refers to the same type of information which is delivered in
444 real-time via an IHD¹². Households can also receive *personalised advice* specific
445 to their living situation on how to lower their electricity consumption, or generic
446 electricity *savings tips*.

447 Studies which provide social feedback are separated into those which provide
448 *social norms* feedback: descriptive feedback of personal consumption compared
449 to that of other households, and *injunctive norms* feedback which provides social
450 approval or disapproval of a household's consumption behaviour.

451 A set of control variables are included in the analysis: *control group*: pres-
452 ence of a control group; *weather controls*: whether weather is controlled for;
453 *demographic controls*: the collection demographic information; *random assign-*
454 *ment*: households are assigned randomly to control and treatment groups as
455 opposed to choosing an intervention; *opt-in recruitment*: households choose to
456 participate in the study; *duration*: duration of study; *year of publication*: the
457 publication year of the study. These control variables are included in order
458 to capture the heterogeneity between the different experiments. Furthermore,
459 studies which include such controls are more robust as they control for changes
460 in behaviour which cannot be explained by the use of an incentive alone.

461 Finally, variables concerning the climate of each study and the average elec-
462 tricity consumption per capita at the time of the study are used as external
463 controls. This is to account for variations between different countries' climate
464 and the impact of a country's consumption, as countries have different electric-
465 ity needs according to their climate, and those with a greater level of average
466 consumption per capita have more scope to reduce their consumption.

467 5. Results

468 5.1. Descriptive Statistics

469 The analysis covers 128 observations from 52 unique papers giving, on av-
470 erage, 2.5 observations per study. In meta-analysis it is preferable to limit the
471 analysis to one observation per study in order to reduce correlation between
472 studies (Nelson and Kennedy, 2009). However, given that some studies describe
473 the results of more than one experiment or simultaneously test different com-
474 binations of incentives, doing so would greatly limit the number of observable
475 treatment effects.

¹²Only data that are received via an IHD are considered to be *real-time feedback* in the present analysis. Real-time data are made available to households via websites (see Houde *et al.*, 2013), however, the data are not accessible to consumers in real-time. They must log-on to the site in order to access the information. The incentives used in such experiments are included in *individual feedback*.

476 Table 3 provides descriptive statistics of the independent and dependent
477 variables for the full sample. Within the sample of studies selected for this
478 analysis, *individual feedback* is the most experimented treatment, representing
479 70% of the observations and 79% of the studies. Compared with previous meta-
480 analyses, the share of studies involving a form of social feedback (*social norms* or
481 *injunctive norms*) has increased. *Social norms* represents 16% of observations
482 and 27% of studies. The *injunctive norms* treatment represents 25% of both
483 the observations and studies.

484 Concerning the design of the primary studies, the majority use a control
485 group for comparison and control for demographic differences in the sample
486 population, 85% and 71% respectively. Fewer studies (48%) control for vari-
487 ations in the weather. Randomised controlled trials are increasingly used to
488 explore the effects of incentives on energy consumption. In the present sample,
489 in 65% of observations, subjects are randomly assigned to a treatment but this
490 is not a practice adopted in all studies, 52%. Opt-in recruitment is the most
491 common method of recruitment, 68% of observations and 71% of studies.

492 5.2. Average Effects by Treatment

493 Table 3 also provides both a non-weighted and weighted average treatment
494 effect (ATE) by incentive. ATE refer to the percentage reduction or increase in
495 consumption for a group of households in response to an intervention. These
496 are the results reported in or constructed from data in the primary study. To
497 calculate the weighted ATE, the reported effect sizes from the primary observa-
498 tions are weighted using the sample size of each primary observation (i.e.: the
499 number of households in a study who face the same intervention) as frequency
500 weights then averaged following Schmidt and Hunter (2014). This gives more
501 weight to observations with larger samples as such studies are considered to
502 show a more representative estimate of the true effect size.

503 The ATE across all incentives is a 3.91% reduction in electricity consump-
504 tion. Once sample sizes are accounted for, the weighted ATE equates to a 1.87%
505 reduction. This means that, on average, an incentive in a typical electricity con-
506 servation study will result in electricity savings of slightly less than 2%. In the
507 sample of studies selected, the effect of incentives on electricity consumption
508 ranges from a 22.2% reduction (Kendel and Lazaric, 2015) to a 13.69% increase
509 (Torriti, 2012).

510 From Table 3, it can be seen that *real-time feedback* and *monetary infor-*
511 *mation* have the greatest effects on electricity consumption with a weighted
512 average reduction in consumption of 2.97% and 2.74%, respectively. *Pricing*
513 *strategies* have the smallest effect on electricity consumption with a weighted
514 average reduction in consumption of 1.03%.

Study characteristic	Mean	Std. dev.	Primary obs.	Primary studies	Sample size	Min (%)	Max (%)	ATE (%)	Weighted ATE (%)
Effect size					5570	-22.20	13.69	-3.91	-1.87
Pricing strategies	0.34	0.47	34%	31%	1670	-14.20	13.69	-3.96	-1.03
Monetary information	0.31	0.47	31%	42%	640	-18.06	5.30	-4.11	-2.74
Individual feedback	0.70	0.46	70%	79%	7765	-22.20	5.30	-4.35	-1.91
Real-time feedback	0.38	0.49	38%	40%	458	-18.06	5.30	-5.01	-2.97
Personalised feedback	0.18	0.39	18%	13%	16525	-12.00	-0.60	-2.55	-2.02
Savings tips	0.48	0.50	48%	37%	4282	-16.71	5.30	-2.86	-1.77
Social norms	0.16	0.36	16%	27%	764	-18.00	3.50	-4.43	-2.24
Injunctive norms	0.25	0.43	25%	25%	19017	-7.02	-1.00	-2.39	-1.95
Control group	0.87	0.34	87%	85%	6399				
Weather controls	0.65	0.48	65%	48%	5710				
Demographic controls	0.80	0.40	80%	71%	5702				
Random assignment	0.65	0.48	65%	52%	7993				
Opt-in recruitment	0.68	0.47	68%	71%	466				
Duration (months)	11.97	9.05	100%	100%	5570				
Sample size	5570	13677	100%	100%	5570				
Number of observations			128	52					

Table 3: Descriptive statistics and average treatment effects

515 To assess how effect size estimates are affected by the conception of a study,
516 the primary studies are separated into those which use a medium level of con-
517 trols (control group, weather and demographic controls) following Delmas *et al.*
518 (2013) and those which use a high level of controls (as before and employ a ran-
519 domised treatment assignment approach and an opt-out recruitment method)
520 following McKerracher and Torriti (2013). Such studies are assumed to show a
521 more representative estimate of the true treatment effect as they control for a
522 greater number of factors which could affect the effectiveness of an intervention.

523 When a control group is used for comparison, additional variations in con-
524 sumption across the duration of a study are accounted for. Controlling for
525 demographic and weather variables allows for the capture of additional factors
526 that may affect energy consumption in addition to the incentives used. Studies
527 which adopt a random treatment assignment method and an opt-out method
528 of recruitment are more representative as they use samples in which households
529 have not chosen their treatment method nor are subject to selection bias.

530 Table 4 gives the ATE and weighted ATE by level of controls used. Of
531 all observations 18% include all five controls, and 38% include at least three
532 controls. The studies with high controls have an ATE of -2.17%, followed by
533 and ATE of -3.56% for medium controls, and those with fewer controls have an
534 ATE of -4.93%¹³. The weighted ATE indicates only marginal differences when
535 sample size is taken into account.

536 Figure 3 shows the distribution of treatment effect by publication year. The
537 majority of studies were published from 2010 onwards. A large number of the
538 studies were published in 2011. There does not appear to be a trend in the

¹³These ATE are significantly different from one another (p -value ≤ 0.01 , Wilcoxon signed rank test).

	Primary obs.	Min (%)	Max (%)	ATE (%)	Weighted ATE (%)
All studies	128	-22.20	13.69	-3.91	-1.87
High level of controls	23	-5.40	-1.17	-2.17	-1.98
Medium level of controls	49	-18.06	1.52	-3.56	-1.99
Low level of controls	56	-22.20	13.69	-4.93	-1.67

Table 4: ATE by number of controls

539 effects of incentives on electricity consumption over this time period.

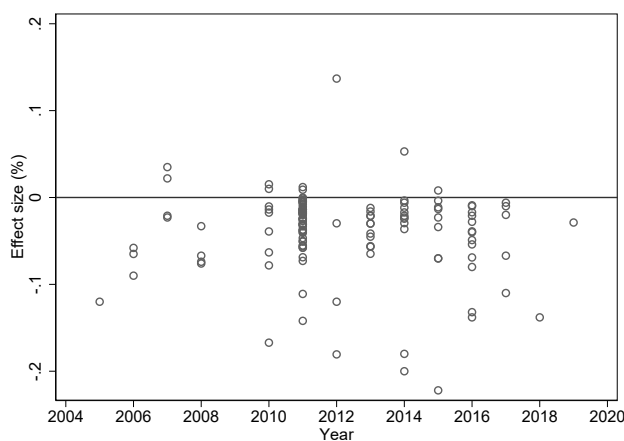


Figure 3: Treatment effect by year of publication

540 Figure 4 shows the distribution of treatment effect by duration of the study.
 541 The majority of observations, 60%, are shorter than 12 months in duration.
 542 There are a cluster of studies lasting two years (13%). The majority of the
 543 longer studies are those that are led by utilities. Finally, there are a few utility-
 544 led studies which last for almost three years. Figure 4 suggests that the longer
 545 the duration of a study, the smaller the effect of incentives on electricity savings.

546 5.3. Publication Bias Analysis

547 According to Card and Krueger (1995) there are three potential sources of
 548 publication bias in economic research: (1) a predisposition to accept studies
 549 which are consistent with the conventional view; (2) an inclination to report
 550 models based on the presence of conventionally expected results; (3) a tendency
 551 to publish only statistically significant results. Given this, meta-analysis fre-
 552 quently suffers from publication bias.

553 Potential publication bias in the sample of primary studies used in this meta-
 554 analysis can be analysed graphically using a funnel plot, as shown in Figure 5.
 555 Funnel plots show treatment effects against a measure of precision, such as the

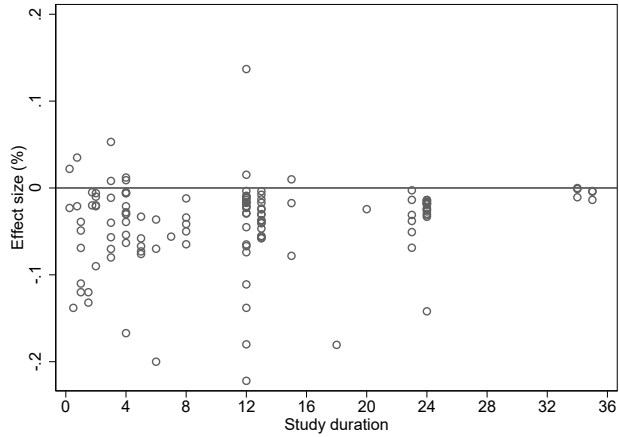


Figure 4: Treatment effect by study duration

556 inverse standard error of the treatment effect or the square root of the sample
 557 size of the treatment group. The intuition is that the accuracy of the treatment
 558 effect increases with the level of precision. Studies with larger standard errors
 559 and smaller sample sizes are dispersed at the bottom of the graph, with the
 560 spread of treatment effects decreasing as standard errors decrease and sample
 561 sizes increase. In the absence of publication bias, the effect sizes are distributed
 562 symmetrically around the mean effect size, resulting in a symmetrical, inverted
 563 funnel-shaped graph (Borenstein *et al.*, 2009). On the other hand, if there
 564 is publication bias, an asymmetrical funnel can result due to an absence of
 565 publications of non-statistically significant results (Egger *et al.*, 1997; Sterne
 566 *et al.*, 2004).

567 The funnel plot in Figure 5 plots effect size against the square root of sample
 568 size¹⁴. The plot shows that the majority of treatments result in a reduction in
 569 electricity consumption. The somewhat asymmetrical nature of the funnel plot
 570 suggests that there may be an issue of publication bias in the present sample
 571 due to relevant studies not being included in the analysis.

572 Stanley *et al.* (2010) suggest that publication bias may be reduced and scientific
 573 inference improved by averaging the treatment effects of the top 10% of the
 574 funnel as these are the most precise estimates. Table 5 shows the non-weighted
 575 and weighted ATE for the top decile and the full funnel plot for both the full
 576 sample and the sub-sample for which standard errors are available¹⁵. Compar-

¹⁴The square root of sample size is used as a proxy for precision as either not all studies report standard errors or standard errors cannot be constructed from the available data.

¹⁵There are 48 observations in the sample for which the standard error is available. This sub-sample is used as a robustness check for issues of publication bias as the standard error is the preferred weight.

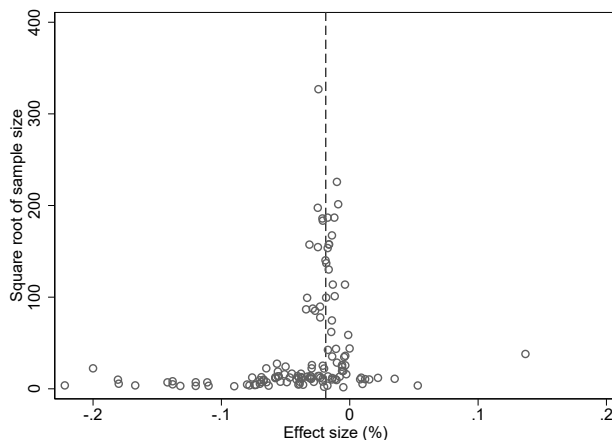


Figure 5: Funnel plot of treatment effect versus sample size

577 ing the ATE for the top 10% of the funnel and the full sample suggests that, on
 578 average, the effect of incentives on electricity consumption is overestimated by
 579 a factor of 2. When sample size is accounted for, as the weighted ATE shows,
 580 the distortion due to publication bias is greatly reduced as the weighted ATE
 581 differ only by 0.02 percentage points.

582 As the inverse standard error is the preferred measure of precision, the non-
 583 weighted and weighted ATE of the 48 observations for which standard errors are
 584 reported or can be constructed are also given. The distortion due to publication
 585 bias for this subset of the sample when comparing ATE between the top 10%
 586 and the full sample is a factor of 2.5. The weighted ATE for the sub-sample
 587 shows a distortion of a factor of 1.35. This suggests that when the preferred
 588 measure of precision is used, which greatly reduces the number of studies, then
 589 publication bias is an issue. In the full sample, publication bias, if present, is
 590 small and not statistically significant once sample sizes have been accounted for
 591 in calculating weighted average treatment effects. Nevertheless, it is prudent to
 592 test for the existence of such bias.

	ATE (%)		Weighted ATE (%)	
	Full sample	Sub-sample	Full sample	Sub-sample
Top 10% of funnel plot	-1.86	-1.27	-1.89	-0.99
All of funnel plot	-3.91	-3.20	-1.87	-1.34
Observations	128	48	128	48

Table 5: Comparison of ATE accounting for publication bias

593 In the presence of publication bias, treatment effects are positively correlated
 594 with their standard errors (Stanley and Doucouliagos, 2012). This suggests that

595 the size of an effect will depend on its standard error:

$$treatment_effect_i = \beta_0 + \beta_1 SE_i + \epsilon_i \quad (3)$$

596 To account for differences in the primary studies, the equation is weighted by
597 a measure of precision, ideally the inverse of its standard error (Stanley *et al.*,
598 2010):

$$t_i = \beta_0(1/SE_i) + \beta_1 + v_i \quad (4)$$

599 where t_i is the t-statistic of the treatment effect. As standard errors are not
600 available for all observations, this equation is also constructed using the square
601 root of sample size as the measure of precision:

$$treatment_effect_i/sample_size_i^{0.5} = \beta_0(1/sample_size_i)^{0.5} + \beta_1 + v_i. \quad (5)$$

602 In the presence of publication bias, treatment effects are positively correlated
603 with their standard errors, and negatively correlated with sample sizes, as
604 standard errors are inverse functions of sample size (Stanley and Doucouliagos,
605 2012; Schmidt and Hunter, 2014). Estimates of β_0 from equations 4 and 5 are
606 an alternative correction of publication bias (Stanley and Doucouliagos, 2012).
607 Table 6 shows the results of the estimations of the models in equations 4 and 5
608 for the sub-sample of 48 studies for which the standard error is present and of
609 equation 5 for the full sample using the square root of sample size as a proxy
610 measure of precision.

611 Testing $H_0 : \beta_1 = 0$ is a test of whether publication bias is present, the
612 funnel asymmetry test. If the coefficient is significantly different from zero then
613 there is publication bias. In the first and second specifications of 6, the null
614 hypotheses are rejected which suggests that there is an issue of publication bias
615 in the sub sample for which standard errors are present. This is unsurprising
616 given the small number of observations for which standard errors are available.
617 In the third specification of Table 6, the null hypothesis cannot be rejected
618 indicating no publication bias in the full sample.

619 A second test is the precision effect test of whether there is a genuine em-
620 pirical effect: $H_0 : \beta_0 = 0$. If the coefficient is significantly different from 0,
621 then there is an underlying effect (Stanley and Doucouliagos, 2012). In all three
622 specifications, the null hypothesis is rejected, implying that there is a genuine
623 empirical effect which merits further analysis.

624 Graphically, the funnel plot suggests that there is a potential issue of publi-
625 cation bias. When comparing the ATE of the full sample to the top 10% of the
626 funnel, this bias is of a factor 2. Testing for publication bias suggests that pub-
627 lication bias is present in the sub-sample for which standard errors are present.
628 In the full sample, the funnel asymmetry test indicates no issue of publication
629 bias. However, this test has been shown to have low power in small samples
630 (Sterne and Egger, 2001). Accounting for sample sizes reduces the distortion
631 due to publication bias to a small and insignificant amount. Therefore, a WLS

632 estimation will be used to mitigate publication bias and to account for het-
633 eroscedasticity in the sample of primary observations, as discussed in Section
634 4.2.

	(1)	(2)	(3)
	Standard error	Square root of sample size	Square root of sample size
	<i>Equation 4</i>	<i>Equation 5</i>	<i>Equation 5</i>
β_0	-0.808*** (0.059)	-7.087*** (0.692)	-6.474*** (2.194)
β_1	-203.631*** (65.878)	0.146** (0.053)	0.070 (0.156)
Observations	48	48	128
R^2	0.816	0.519	0.374

Standard errors in parentheses

Standard errors are clustered by primary study.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Estimation of publication bias

635 5.4. Effects of Individual Incentives

636 Table 7 shows the results of the WLS meta-regression analysis across the
637 different incentive types. Specifications 1 and 2 consider monetary incentives,
638 specifications 3 and 4 look at personal feedback, specifications 5 and 6 present
639 social feedback, specifications 7 and 8 include study design variables, and fi-
640 nally specifications 9 and 10 are of the full model. Odd numbered specifications
641 present the coefficients of the listed variables, and even-numbered specifications
642 also control for external factors which may influence energy consumption be-
643 haviour including the energy consumption per capita and the climate conditions
644 of the country in which the study took place¹⁶. In addition, each specification
645 includes a variable accounting for the duration of the study and the year of
646 publication. Finally, standard errors for each estimation are clustered by study
647 to account for any dependence between studies. Coefficients on the different
648 incentives are interpreted as a change in electricity consumption relative to the
649 consumption of the control group, when present in the study (which is the case
650 for 87% of the observations) and controlled for in each specification, or the
651 baseline level of consumption. A negative coefficient signifies a reduction in
652 electricity consumption.

653 In specification 1, there is no significant effect of monetary incentives on con-
654 sumption behaviour. Controlling for external factors (specifications 2 and 10)
655 and for other incentives (specification 9 and 10), the effect of *monetary infor-*
656 *mation* is significant showing an increase in electricity consumption of between
657 2.3 and 3.5 percentage points.

¹⁶Energy consumption per capita data was collected from International Energy Agency (2019) with observations categorised into groups by quartile. Observations are categorised into climate type according to the Köppen Climate Categorisation (Arnfield, 2019).

658 *Individual feedback* has a significant negative effect indicating a reduction
659 in electricity consumption of 2-4 percentage points. In the personal feedback
660 specifications (3 and 4), when such feedback is delivered in real-time no ad-
661 ditional significant effects on electricity consumption are found. This could
662 indicate that the effectiveness of feedback is captured in the individual feedback
663 variable, however, when controlling for all incentives and for external factors,
664 *real-time feedback* shows an energy reduction effect of 2.4 percentage points.

665 The use of *savings tips* indicates an increase in consumption of 3.2 to 5.2
666 percentage points across all specifications. *Personalised advice* has a significant
667 effect of reducing energy consumption when external factors are controlled for,
668 of 5.2 percentage points.

669 Concerning the design of the study, across specifications 2-10, the coefficient
670 on *control group* is significantly positive. This suggests that when electricity
671 savings are calculated compared to a baseline of the same group (which is the
672 case for 13% of observations), they may be overestimated by between 4.3 and
673 10.1 percentage points. Studies which do not account for the demographic
674 characteristics of their sample may overestimate energy savings by between 3.2
675 and 5.5 percentage points. Concerning the method of recruiting households
676 to participate in the study, those which recruit volunteer households, *opt-in*
677 *recruitment*, achieve greater energy savings by 3.0 to 5.5 percentage points.

678 Finally, the coefficient on *year of publication* is significantly negative in
679 odd-numbered specifications, indicating that more recent studies show slightly
680 greater levels of reduction of the order of 0.6 percentage points. However, once
681 external factors are controlled for, this significant effect disappears.

682 For clarity, Table 8 summarises the results presented in this section against
683 the different hypotheses presented in Section 2 and 3. The status of each hy-
684 pothesis in relation to the corresponding result is given.

685 6. Discussion

686 A reduction in household electricity consumption in response to incentives
687 is necessary to create a more flexible energy demand to allow for greater inte-
688 gration of renewable energy sources in the production mix and to meet climate
689 change objectives. This meta-analysis set out to collate the recent experimental
690 evidence on the effect of different incentives and experimental design features
691 on residential electricity consumption.

692 The extensive research for studies resulted in a sample of 52 studies with
693 128 observations of more than 713 002 households across 13 countries over 15
694 years (2005-2019). This equates to nearly 3.5 studies per year highlighting the
695 increased interest in this topic in recent years. Previous analyses and reviews
696 collected at most 1.5 studies per year (Ehrhardt-Martinez *et al.*, 2010; Delmas
697 *et al.*, 2013). In this section, the main findings are discussed followed by the
698 limits of the present analysis.

699 Firstly, on average, an incentive can be expected to result in a reduction
700 in energy consumption of 3.91%, varying between 2.4 and 5.0%. This result

	Monetary (1)	(2)	Personal feedback (3)	(4)	Social feedback (5)	(6)	Study design (7)	(8)	(9)	Full (10)
Incentives										
Pricing strategies	-0.569 (1.382)	-0.407 (1.547)							-0.933 (1.318)	-0.038 (1.226)
Monetary information	1.932 (1.537)	2.331* (1.357)							3.362** (1.541)	3.482** (1.316)
Individual feedback			-2.158* (1.283)	-0.784 (1.054)					-4.098*** (1.456)	-2.497* (1.253)
Real-time feedback			-0.388 (1.314)	-1.051 (1.283)					-1.738 (1.287)	-2.370* (1.323)
Savings tips			3.743** (1.498)	5.191*** (1.752)					3.188** (1.390)	4.761*** (1.584)
Personalised advice			-3.472 (3.405)	-5.167* (2.641)					-4.443 (2.966)	-5.213** (2.130)
Social norms					-1.788 (2.205)	-2.384 (2.001)			0.522 (1.666)	-0.255 (1.580)
Injunctive norms					0.236 (1.599)	-0.703 (1.584)			1.133 (1.831)	0.067 (1.588)
Study design variables										
Control group	3.285 (2.440)	4.265* (2.355)	8.215*** (2.671)	10.116*** (2.591)	4.324* (2.423)	5.954*** (2.220)	4.424* (2.525)	5.783** (2.432)	7.354*** (2.355)	8.893*** (2.358)
Weather controls	1.200 (1.619)	0.549 (1.561)	-0.857 (1.648)	-1.816 (1.574)	0.692 (1.678)	-0.023 (1.542)	0.570 (1.711)	-0.111 (1.586)	-0.115 (1.713)	-1.234 (1.587)
Demographic controls	4.659** (2.121)	5.495** (2.188)	3.210* (1.807)	3.749** (1.637)	3.769** (1.669)	4.214** (1.867)	3.945** (1.751)	4.449** (2.103)	4.622** (1.904)	5.449*** (1.730)
Random assignment	0.605 (1.591)	-0.136 (1.573)	-0.708 (1.880)	-0.952 (1.669)	0.412 (1.669)	-0.254 (1.626)	0.451 (1.588)	-0.335 (1.636)	-1.031 (1.654)	-1.009 (1.477)
Opt-in recruitment	-4.731** (1.981)	-5.050** (2.040)	-3.037 (2.222)	-4.274** (1.745)	-3.878 (2.417)	-4.316* (2.406)	-4.094** (1.746)	-3.916* (2.010)	-3.353 (2.758)	-5.517** (2.234)
Duration	-0.078 (0.118)	0.010 (0.124)	-0.006 (0.100)	0.107 (0.112)	-0.071 (0.116)	0.032 (0.120)	-0.060 (0.113)	0.039 (0.120)	-0.007 (0.100)	0.081 (0.113)
Year of publication	-0.621** (0.306)	-0.465 (0.343)	-0.635** (0.285)	-0.409 (0.295)	-0.659** (0.315)	-0.473 (0.364)	-0.686** (0.315)	-0.543 (0.352)	-0.541** (0.269)	-0.298 (0.295)
Constant	1241.540** (615.561)	923.988 (689.824)	1266.243** (574.260)	808.435 (593.854)	1316.871** (633.507)	942.315 (730.818)	1370.837** (633.091)	1081.165 (706.105)	1077.616* (540.597)	585.391 (592.914)
Energy cons. per capita controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Climate type controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Adjusted R^2	0.178	0.225	0.294	0.376	0.168	0.215	0.168	0.208	0.322	0.399
Number of clusters	52	52	52	52	52	52	52	52	52	52
Observations	128	128	128	128	128	128	128	128	128	128

Standard errors in parentheses are clustered by primary study.
Inverse square roots of sample size are used as analytical weights.
A negative coefficient reads as a reduction in energy consumption.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: WLS estimation of treatment effects

Hypothesis	Hypothesis status	Empirical result
H1	Unconfirmed	Pricing strategies have no significant effect Monetary information increases consumption
H2	Partially confirmed	Individual and real-time feedback, and personalised advice lead to energy conservation Savings tips increase consumption
H3	Unconfirmed	Social and injunctive norms have no significant effect
H4	Confirmed (graphically)	The funnel plot shows that studies with larger samples have smaller effect sizes
H5	Partially confirmed	Studies without controls groups and which do not control for demographic characteristics overestimate energy savings Studies which use opt-in recruitment achieve higher energy savings than those which do not Weather controls and random treatment assignment have no significant effect
H6	Partially confirmed	More recent studies show marginally greater levels of energy savings, but this is no longer significant when controlling for external factors

Table 8: Summary of results in relation to hypotheses

701 is at the lower end of results reported in previous meta-analyses (see Table 1).
702 However it is in line with the conclusion of McKerracher and Torriti (2013)
703 that there is a downward trend in the size of conservation effects. Accounting
704 for variation in sample sizes, as the publication bias analysis suggests, a study
705 will show on average a reduction in consumption of 1.87% which is a more
706 conservative estimate.

707 Secondly, consumption feedback relative to one’s own consumption and that
708 which is accessible in real-time effectively reduce consumption. The majority of
709 households are unaware of their electricity consumption and of how much elec-
710 tricity different daily activities consume. By providing households with detailed
711 consumption information, their awareness of their own consumption increases
712 and this motivates households to lower their consumption. Personalised advice
713 is also seen to reduce consumption, however, such interventions require higher
714 involvement from third parties. In order to provide households with tailored
715 advice on what they can do to lower their consumption, and for such interven-
716 tions to be cost-effective, a large amount of information on households would be
717 required (occupancy information, what sort of appliances are in the household,
718 characteristics of the house, etc.). Qualitative research finds that households
719 are typically against the collection of such detailed data about themselves and
720 its use by energy companies or third parties (Gerpott and Paukert, 2013; Naus
721 *et al.*, 2014; Pepermans, 2014; Richter and Pollitt, 2018).

722 Thirdly, households increased their consumption in response to monetary
723 information on consumption. This result is consistent with studies which have
724 found that the possible monetary savings from lowering energy consumption

725 are too small to motivate behavioural change (Hargreaves *et al.*, 2010; Goulden
726 *et al.*, 2014), or that households expenditure on electricity is small relative to
727 their income (Faruqui *et al.*, 2010; Schleich *et al.*, 2013; Murtagh *et al.*, 2014).
728 Upon receiving monetary information, if households are spending less than anti-
729 cipated they may feel entitled to increase their consumption. Prior to receiv-
730 ing such information, households may have been driven by other motivations to
731 lower their consumption, thus increasing the salience of the monetary cost of
732 consumption may crowd out intrinsic motivations (Farrow *et al.*, 2017).

733 Fourthly, providing households with generic advice on how to save electricity
734 has the undesired effect of increasing consumption. This result can be explained
735 by reactance theory (Brehm, 1966; De Young, 2000), or that the reminder of
736 what a household should do may crowd out any existing pro-environmental
737 motives to do so.

738 Finally, the experimental quality of recent studies has considerably improved.
739 Delmas *et al.* (2013) found that merely 15% of their sample of studies used a con-
740 trol group, and controlled for both weather variations and the socio-demographic
741 characteristics of the participating households. In the present analysis, 56% of
742 the sample of studies use this level of controls, and 18% go further by recruiting
743 households on an opt-out basis and by using a randomised approach to assign-
744 ing household to treatments. Despite this increase in the level of controls used,
745 not all studies are as methodological rigorous. They do not use sufficient con-
746 trols (Van Dam *et al.*, 2010; Bartusch *et al.*, 2011; Vassileva *et al.*, 2012; D’Oca
747 *et al.*, 2014), use small samples (Ueno *et al.*, 2006; Vande Moere *et al.*, 2011;
748 Bradley *et al.*, 2016), test an incentive over a short time period (Schultz *et al.*,
749 2007; Nguyen *et al.*, 2016), or suffer from self-selection bias (Nilsson *et al.*, 2014;
750 Kendel and Lazaric, 2015). This lack of controls and experimentation of incen-
751 tives with a small number of volunteer households over a short time frame lead
752 to higher estimations of the reduction potential of different incentives which may
753 not be reflective of their true effect. In particular, volunteer households may
754 have motivations to take part in studies that are not necessarily accounted for in
755 the experiment. These participants may be predisposed to make a greater effort
756 than if the incentive were to be implemented at a national level (Alexander,
757 2010; Ericson, 2011).

758 7. Conclusion

759 This paper has brought the knowledge on the effectiveness of incentives on
760 residential electricity consumption up-to-date by analysing the results of stud-
761 ies across the fields of economics, psychology, marketing and building research
762 within the "Smart-Grid Era". On average, an incentive designed to reduce
763 household electricity consumption will result in a reduction in consumption of
764 3.91%. Accounting for differences in sample sizes, a more conservative estimate
765 suggests a reduction of 1.87%. This result indicates that electricity consump-
766 tion reductions can be attained by incentivising households to make behavioural
767 changes to reduce their electricity consumption.

768 Information on households own consumption delivered via paper bills, on-
769 line or in real-time, and personalised advice are found to be the most effective
770 at lowering residential electricity consumption. Information provided in mon-
771 etary terms and generic savings tips are shown to have the adverse effect of
772 increasing electricity consumption. Other incentives namely pricing strategies
773 and behavioural incentives do not significantly affect on consumption. However,
774 disentangling the effects of individual incentives is complicated by confounding
775 effects as few studies examine the effect of a single incentive.

776 The present meta-analysis faces certain limits. As with all meta-analyses,
777 the present paper is limited by the data available. While every effort was made
778 to be exhaustive in the collection of primary studies, appropriate studies may
779 have been missed. Furthermore, the analysis highlighted the methodological
780 shortcomings of some studies which may lead to uncertainty as to the reliability
781 of their reported effect sizes. Certain primary studies found treatment effects
782 which were much larger, in both the direction of reducing and of consuming more
783 electricity. Such results should not necessarily be excluded from the dataset as
784 they meet the criteria set out in Section 4.1, however, they may influence the
785 findings and conclusions of the analysis.

786 Secondly, the primary studies differ in the statistical procedures used to
787 calculate effect sizes. This information is not always clearly presented in the
788 primary studies and ranges from simple percentage change calculations between
789 either a baseline and a treatment period, to difference-in-difference estimations,
790 to econometric analysis accounting for household fixed effects.

791 Thirdly, the primary studies may differ in ways that are not captured in the
792 present analysis. For example, the composition of the participating households,
793 the level of involvement of researchers in the study to increase household en-
794 gagement, the amount of detail in feedback from monthly to appliance specific
795 data, the frequency of feedback delivery or consultation of IHDs, the way in
796 which households pay for their electricity, etc. Such information can be difficult
797 to collect and is not necessarily comparable across different incentives. Future
798 analyses could focus on how the intensity of delivery of a particular incentive
799 affects its effectiveness. Particularly in the case of IHD as previous studies have
800 found that while households may initially interested in the data provided they
801 soon lose interest and no longer consult the information (Hargreaves *et al.*, 2010;
802 Schleich *et al.*, 2013).

803 Finally, while meta-analysis allows the researcher to calculate effect sizes
804 for individual incentives, in reality, there are few studies which investigate the
805 effect of a single incentive which may lead to confounding effects. Here the
806 conclusion of Andor and Fels (2018) is reiterated: future studies should explore
807 the effectiveness of an individual incentive by applying a single intervention to
808 a treatment group.

809 Given the findings of the present analysis and the limits identified above,
810 several recommendations for future studies can be made. Future studies should:

- 811 • Include a control group in which subjects do not receive an incentive and
812 are monitored at the same time as the treatment group

- 813 • Control for weather variations, in particular the number of days of tem-
814 perature extremes
- 815 • Collect socio-demographic information on households
- 816 • Limit selection bias by recruiting households on an opt-out basis or by the
817 randomisation of treatment assignment
- 818 • Explicitly report statistical procedures to allow for better replication and
819 interpretation of results
- 820 • Improve reporting of details of the experimental procedure
- 821 • Focus on individual incentives to disentangle treatment effects

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