Better off with less (energy)? Household activities during interventions

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Abstract

The dominant supply side perspective in energy research tends to focus on the downsides of (energy) consumption, its costs and the environmental impact. We seek to inform this debate with a reversal of perspective. What are the benefits of energy for the users and how does demand reduction affect them?

We have collected over 18,000 simultaneous records of UK household activities, enjoyment and electricity consumption. These data give us novel and nuanced insights into the relationship between what we do, how much (electricity) we consume at the time and how this affects our sense of enjoyment.

Three broad and interrelated trends emerge:

1. Periods of high activity coincide with high demand
2. Periods of high demand coincide with greater enjoyment (!)
3. Interventions to reduce demand can lead to reductions in demand, but also affect activities and enjoyment

Our ongoing research on demand interventions found that requests to reduce demand during peak periods (57pm) led to 15 % reduction in load. Food related activities have been identified as particularly relevant during peak demand. They tend to get shifted or suppressed and substituted with other activities to compensate. For some, this can lead to increases in enjoyment, while others have their enjoyment reduced, especially where 'quality time' activities are scarified during such interventions.

While the overall trend is for periods of high consumption to be more enjoyable, there are important nuances to consider. We will present high-energy low-enjoyment patterns as well as low-energy high-enjoyment activities. Interventions to reduce the former or increase the latter may hold the key to more acceptable public policies and may even increase well-being.

Three activities that stand out as the most enjoyable are reading, socialising and sleeping. These are also among the least energy consuming. Instead of denying or penalising energy use, encouraging activities like reading, socialising and sleeping could bring about a wide range of benefits, aside from displacing less enjoyable, costly and environmentally harmful demands.

Introduction

With dramatic reductions in the cost of renewable generation, a key challenge for the decarbonisation of electricity may shift from the cost of generation itself, towards the cost of ensuring that electricity can be provided to meet demand in time and space.

Significant costs for storage or other means of flexibility may have to be born by electricity users if demand patterns do not change, or – as projected in many parts of the world – electrification of heating and transport could increase peak demands further.

Demand response is a popular notion to minimise these costs. However, the dynamics underlying current and potential future load profiles are not well understood, inhibiting our ability to project how far demand side response measure may contribute towards system integration of significant shares of renewables.

Thus far most approaches are grounded in traditional engineering and economic theory (National Infrastructure Commission (2016)). They classify appliances as flexible or assume a certain level of price elasticity (Roscoe and Ault (2010)). Based on these principles demand side response can be achieved with automation and tariffs. The UK regulator Ofgem expects automation and time based tariffs to be popular with the general public (Ofgem (2015)), while much social science literature suggests that this may not be the case (Reiss and White (2008), Reis (2018), Darby (2013), Dickman (2017), Löfström (2014)).

To inform the debate on the potential and appropriate means to realise demand side response, we take a detailed look at the dynamics of household electricity use and explore flexibility of this demand in controlled experiments. With this body of work we seek to address two questions:

1. Which activity patterns are responsible for high peak time electricity consumption?
2. How do these patterns change when attempting to reduce peak time consumption?

The first question is addressed in Satre Meloy (2019) using data from the METER study (Philipp Grünewald et al. (2017)), which collected 18,000 pairs of activity and electricity data thus far. Satre Meloy concludes that the timing and practice of food preparation and eating hot meals are a major contributing factor in evening peak demand.

Figure 1. Example of the app interface.

This paper focusses on the second question using new pilot study data in which households were asked to reduce consumption during the typical UK peak demand period from 5pm to 7pm.

Methods and Data

The data collection method is explained in detail in Grünewald and Layberry (2015) and Grunewald (2017). For a period of just over a day all household members above the age of eight are invited to report their activities and their enjoyment of these activities using an app (Figure 1). The app is pre-installed on smartphone-like devices with the sole function of recording activities. A small booklet explains the use of the app and gives tips on how to record common activities. As an encouragement, up to five stars light up at the top of the screen for the completion of 25 activity records. While it is possible to record appliances explicitly, the app focuses on activities in the first place. If a desired activity is not available, custom entries can be typed up in free-text.

At the same time the household electricity use is measured at the mains meter with one second resolution using a clip on electricity recorder. The device is fully automated and free of switches, making the installation as simple as possible for householders themselves. It does deliberately not provide feedback to the user. The data collections spans 28 hours from 5pm to 9pm the next day. This period conveniently covers two of the UK peak demand periods, typically between 5pm and 7pm. We will refer to each of these 28 hour periods as a 'study day'. At the end of the collection period participants return the electricity and activity recorders in a pre-paid envelope for analysis.

The sample of the METER study is a convenience sample and consists of volunteers opting in. An incentive for participation is the chance to win a year free electricity. No other incentives are offered. The socio demographic data suggests that the sample is biased towards affluent households (Grunewald and Diakonova (2018)) with a high interest in energy related matters. Nearly half of participants (46 %) state that they are "very interested" in energy, with a further 30 % claiming to be "interested".

The subset of data for this pilot study was recruited with a leafleting campaign in the West Oxford area in cooperation with a local community group (Low Carbon West Oxford).

The study was advertised as the West Oxford Energy Street Challenge (WOSC), where "the street that responds best to our request to change [their] electricity use" can win prizes. The nature and odds of the prizes was kept deliberately vague as not to raise expectations. Nor was the type of change specified until a few days before the study day. It did, however, appeal to a sense of street competition and asked people to "help your neighbours win the challenge".

Each household was invited to take part on four days in July 2018, from Sunday at 5pm until Monday at 9pm. While this is not the time of year for national peak demand, some similarities in activity patters can be observed throughout the year. A more detailed analysis of seasonal factors is not part of this paper in will follow as part of ongoing data collection. It was for the household to motivate other household members (partners, spouses, children…) to participate. 28 households with 74 people joined the challenge. None of these dropped out, except for absences on three study days due to holidays.

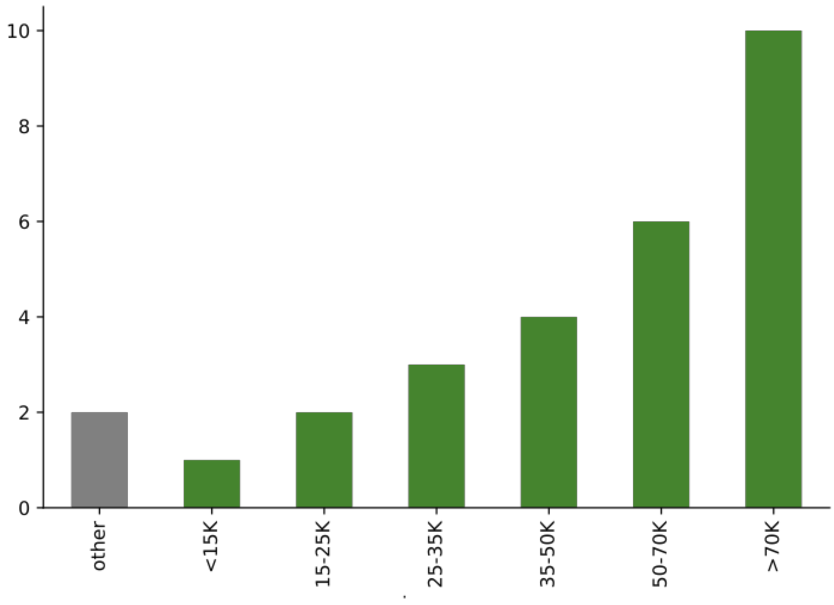

Figure 2. Histogram of number of households by gross annual income.

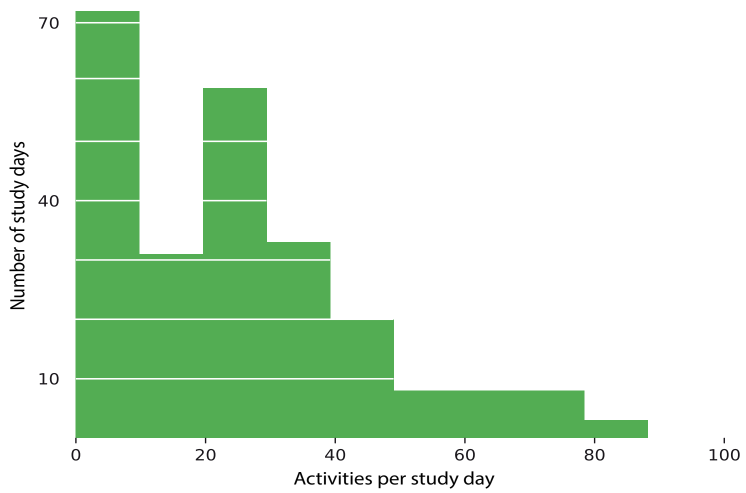

Figure 3. Histogram of the number of reported activities.

The dominance of affluent households is apparent from the histogram of the number of households in Figure 2. This may be a combination of the bias observed in the wider sample and particularly high house prices in this region.

Participants reported on average 29 activities per study day, resulting in 6046 activities for this analysis. Not in all cases did all household members take part. Every household returned at least one valid activity recorder, while 16 % of activity recorders were returned without data.

The distribution of reported activities is shown in Figure 3. 25 activities is the target set by a star reward scheme. Up to 5 golden start light up at the top of the app for reporting 25 activities (see Figure 1). This incentive appears to be effective.

This challenge differed from the conventional METER approach in that household had to repeat their study day four weeks in a row. Figure 4 shows the fatigue resulting in decreases from 32 to 19 activities reported per study day.

On the 1st and 3rd day no changes were requested and participants were asked to go about their day 'as normal'. On the 2nd and the 4th study day the intervention consisted of a note to participants via email and in the post a few days before. Each time it stated "Try to use less electricity from 5pm to 7pm on Monday. This is where you are competing with other streets in the neighbourhood. Things to avoid might be: dish washers, washing machines, electric cookers, etc." For comparability all study days are Sunday to Monday.

As participants were not aware the week before what the intervention would be the next week, it is reasonable to assume that they could not game the study (by deliberately using more at certain times).

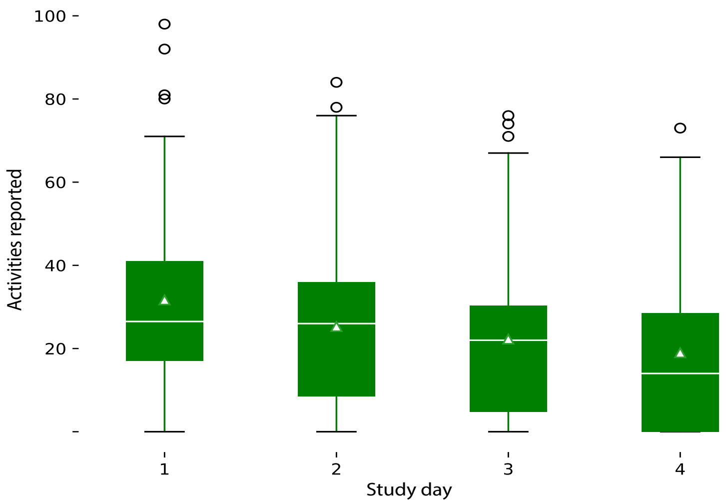

Figure 4. Decline in activity reporting over the four study days.

Results

Each household was measured for two study days without an intervention and two days with the intervention.

We present three metrics to assess the effect of the intervention. Firstly, we compare average power during the 5–7pm period on intervention and non-intervention days. Secondly we compare the change in the ratio of peak time use (5pm–7pm) to average consumption to assess whether the measure was effective at flattening a household's load profile. Finally, we observe any evidence for load shifting to adjacent hours.

CHANGE IN ELECTRICITY USAGE

The relative change in electricity consumption is calculated as

$$r = \frac{P_{ni} - P_i}{P_{ni}}$$

where *P* is the average power for all households between 5 and 7pm on intervention days (*i*) and non-intervention days (*ni*).

The average electricity use for all households between 5 and 7pm is 582 Watt. On intervention days consumption was suppressed by 90 Watt to 492 Watt. In relative terms this is a reduction of = 15 %.

REDUCTION OF THE PEAK-TO-AVERAGE RATIO

To calculate the Peak-to-average ratio (p2a) we divide the average power during the second evening (5–7pm) by the average power over the entire study day. This process normalises households with high or low overall use. A change in use is calculated by subtracting non-intervention averages from intervention averages. Negative values mean that demand has decreased during the intervention. Statistics are first calculated on the level of individual households, and then averages are taken over all the households. That way we account for households that may not have taken part all four times.

$$r_{p2a} = \frac{\sum_{h \in H} \frac{p2a(ni) - p2a(i)}{p2a(ni)}}{N},$$

where *H* is the set *N* households who recorded at least one day with intervention (*i*) and one day without (*ni*). The *p2a* for this household is averaged over the respective study days.

The average household reduction is r_{p2a} = 11 %. The distribution across households is shown in Figure 5. The paired t-test of r_{p2a} is 0.06, making the flattening effect close to being 95 % statistically significant, even within a relatively small sample.

LOAD SHIFT TO ADJACENT HOURS

While some households may respond to the intervention by simply avoiding electricity use, much literature suggests that households would respond to interventions by shifting load to other times, either just before or after the intervention.

To test this effect we compare the average usage in the two hours that precede and follow the 5–7 period. The difference is computed as the fraction between the average peak time usage, and the average from 3pm-5pm and 7pm to 9pm, respectively, relative to non-intervention days.

This metric produces the greatest effect with r_{shift} = 16 % and high statistical significance of p = 0.009. These figures suggest that some shifting is indeed taking place. The number of households shifting from the peak period to adjacent periods (reduction) and vice versa (increase) is shown in Figure 6.

CHANGE IN ACTIVITIES

The findings above are broadly consistent with previous studies (J. Schofield et al. (2014), CER (2011), Sarah J. Darby and McKenna (2012)), with the notable difference that no monetary incentive was required to achieve them.

Having established that shifting has taken place, the focus can now turn to the mechanisms by which this was achieved.

The novel insights from the activity based approach stem from our ability to investigate not just how much demand was changed, but how this change was realised. What sacrifices had to be made? Which patterns are flexible, which ones do not yield to interventions? And what substitutes are put in place for suppressed activities, if any?

The most striking example of load shifting is shown in Figure 7. Within our sample washing machines are normally used

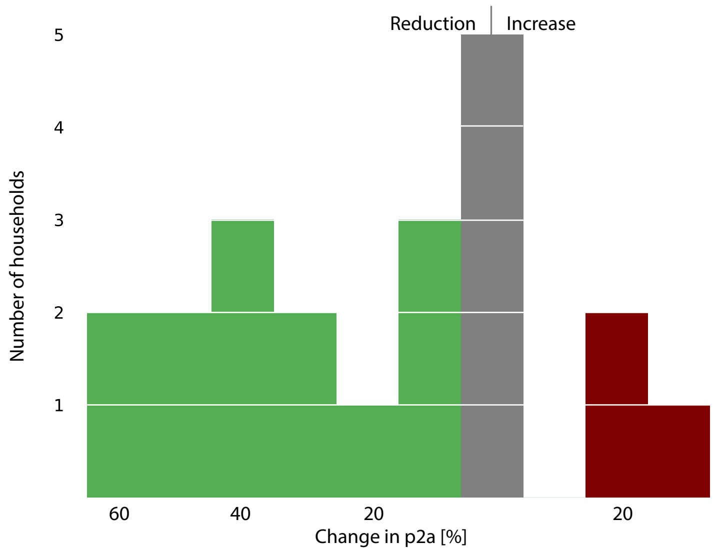

Figure 5. Household histogram of change in Peak-to-Average during the intervention. Mean 11 % reduction.

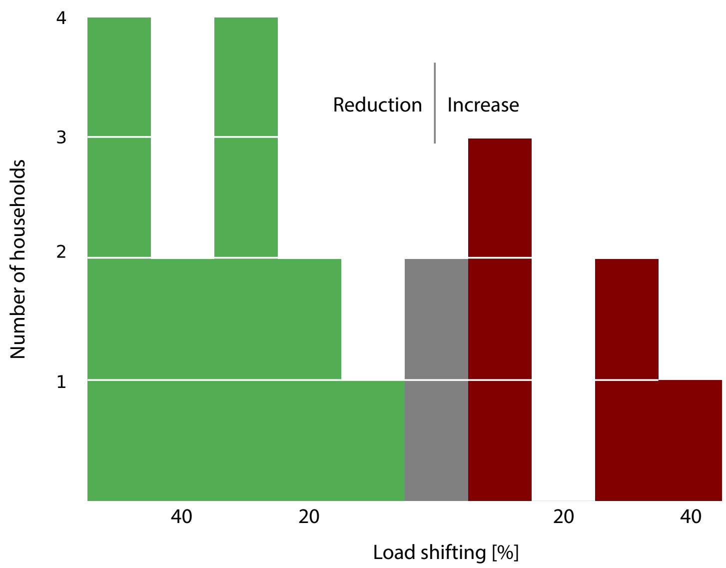

Figure 6. Histogram of load re-allocation from peak period to adjacent hours. (Reduction means load shifted from peak to adjacent period).

mostly before 7pm. The intervention had a profound effect on this pattern. Use before the intervention period halved and during it usage disappeared altogether. The period after 7pm, which was not used before, sees a steep increase. Washing machine use, based on these data, is highly amenable to load shifting to a later time.

Satre Meloy (2019) has shown that peak time usage is strongly linked with hot meals. Figure 8 shows how hot meals respond to the intervention. The conventional pattern is for about a third of hot meals to be reported between 5 and 7pm, and about twice as often after this period. The intervention has had a profound effect here, too. Both during and after the 5–7pm window the reporting of hot meals has markedly reduced. For hot meals to be affected even after the intervention period is quite reasonable, since meal preparation would have had to take place in advance.

Ovens, which are a commonly reported in advance of 'eating a hot meal' confirm this pattern (Figure 9). Their use more than halves during the intervention and is still suppressed afterwards. Hot meal preparation was avoided altogether for those evenings in some households.

The WOSC data gives a fascinating insight into how households coped with the restriction on hot meals. Figures 10 and 11 show the change in reporting of snacks and hot drinks. Fewer snacks are reported before and after interventions, but more during the intervention, when people would have had a hot meal. Even more pronounced is the effect on hot drinks. During the intervention the reporting frequency more than tri-

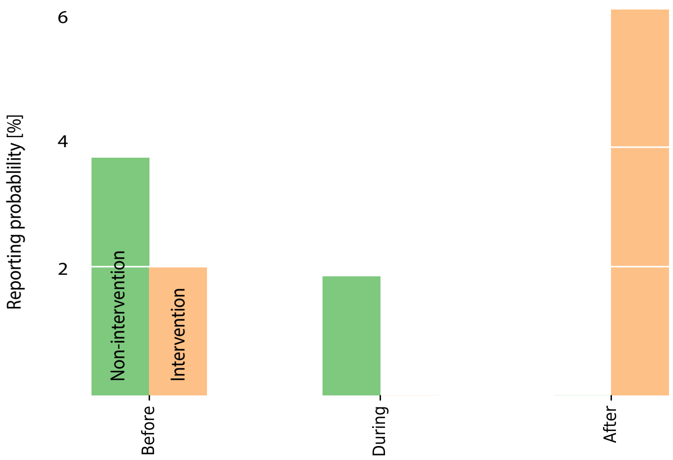

Figure 7. Shift of washing machine use to after the intervention period.

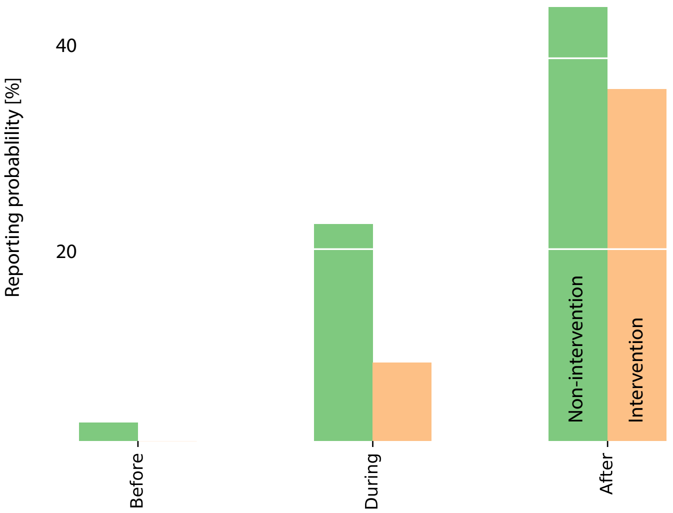

Figure 8. Reduction of hot meals on intervention days.

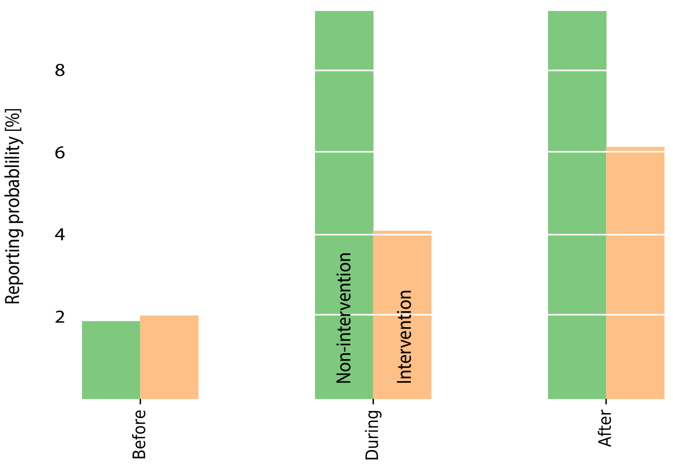

Figure 9. Avoided oven use on intervention days.

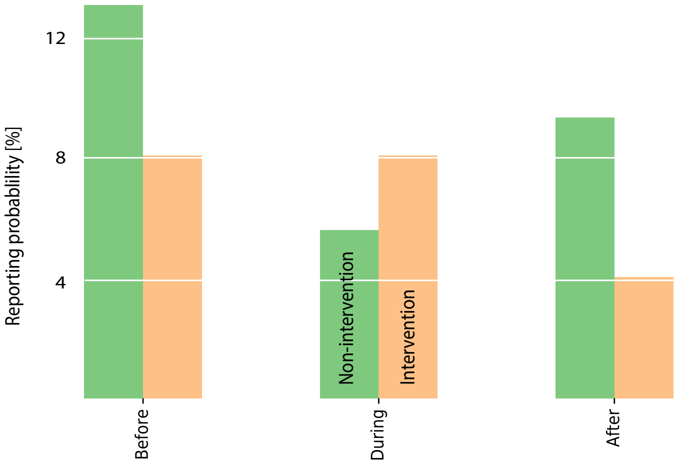

Figure 10. Reporting of snacks.

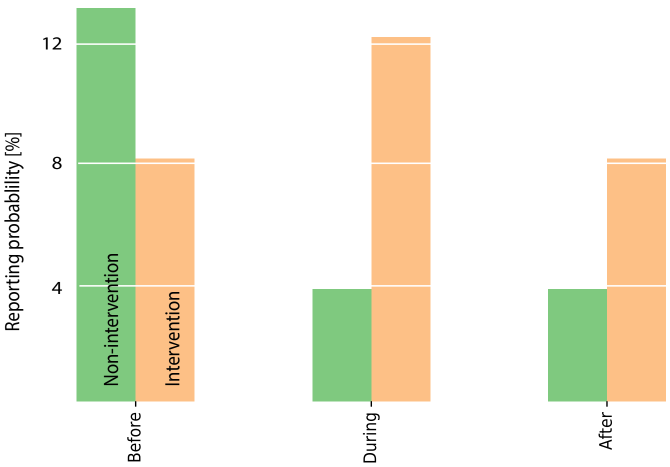

Figure 11. Reporting of hot drinks.

pled and even after the intervention it is still twice as frequently reported. These are strong indicators that hot meals are substituted with snacks and hot drinks.

Discussion

One hypothesis we set out prior to this pilot study was that interventions would restrict participants in their activities and therefore result in a reduction of their enjoyment. While it is true that hot meals are among the activities with the highest reported enjoyment (ranked 3rd behind reading and socialising with 4.6 on our 5 point scale, see Figure 12), the suppression of hot meals has not resulted in a statistically significant reduction of enjoyment overall. Two possible explanations can be considered. Firstly, the meal was often substituted with another very enjoyable activity. Hot drinks still score 4.4 out of 5. Secondly, the pronounced displacement of chores, such as use of the washing machine, which scores among the lowest in enjoyment with 3.2 may help to balance some of the enjoyment figures.

With the right incentives it may therefore be possible to shift electrical loads without negatively affecting the enjoyment of energy service users.

The second observation, which is worthy of further discussion is the nature of the incentive. The conventional and dominant approach in the literature on load shifting is a price incentive in various forms of time based tariffs (J. R. Schofield (2015),Fell et al. (2015),Thumim (2014)). In this study no monetary incentive was used and response rates of similar or greater magnitude have been recorded. For policy makers, suppliers and retail market designers it may be worth considering whether non-monetary incentives (be they information, gaming/competition or symbolic rewards) could be an effective alternative or complement to pure tariff based approaches.

The data presented here is merely a pilot study. We have been careful not to read too much into the activities and load patterns of individual households. All these data have significant variability, diversity and potential biases. A larger sample is

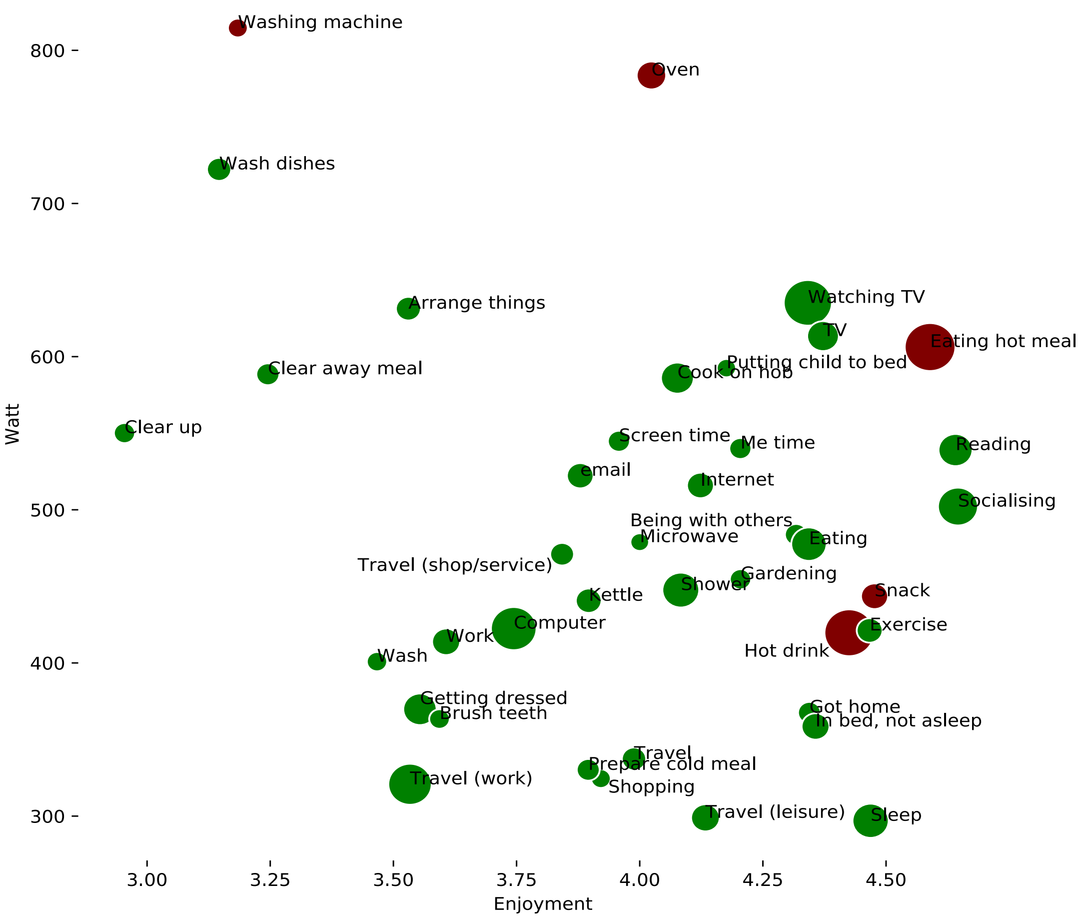

Figure 12. Enjoyment of activities and their energy intensity. Activities discussed here are shown in red (dark). Limited to at least 100 mentions. Size is proportional to frequency of reporting. N = 11,286 activities.

currently being collected and more detailed and robust finding may be deduced in future.

Further research is needed to learn just how sustainable this demonstrated flexibility is. While participants on the whole responded by modifying their activities as part of a controlled study, it is less clear whether they would be as receptive to similar requests coming from commercial actors, such as utilities or aggregators. Factoring flexible response into their lives, unaided by novelty or competition elements, might prove a somewhat harder task.

Conclusions

We have presented the first study of its kind, observing load as well as activity responses to electricity use interventions at household level. Voluntary recruitment with no explicit financial incentive was successful in winning 74 participants to take part for up to four times and report over 6,000 activities. The sample and it's scale do not allow for nationally representative extrapolations, but clear trends are apparent.

A simple request, appealing to street level competition, led to statistically significant reductions in demand (15 %), a flattening of the peak-to-average load shape (11 %) and load shifting (16 %).

The changes in electricity use could be attributed to particular shifts in activity patterns. Washing machine use and hot meal routines were particularly affected. The sacrifice of hot meals appears to be compensated for with an increase of snacking and hot drinks.

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