

# Disaggregated Consumption Feedback and Energy Conservation: Evidence from a Randomized Controlled Trial

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A Toxa  
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## Background

- Consumers are imperfectly informed about the inputs required for energy services
- Feedback can foster consumer learning and induce behavioral change (e.g. Jessoe & Rapson 2014)
- Aggregated feedback has only limited potentials (Buchanan et al. 2015, Degen et al. 2013)
- Potential solution: behavior-specific feedback (Tiefenbeck et al. 2016, Ascensio & Delmas 2015)

# Background

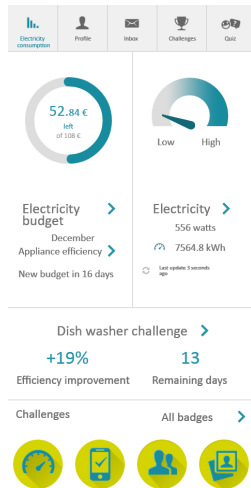
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## Research question

What is the impact of disaggregated appliance use feedback on electricity consumption?

# Approach and main findings

- We randomize information provision on a smartphone app
- Disaggregated feedback reduces electricity consumption strongly in the short run ( $\approx 10\%$ )
- Conservation effect for at least 6 months, yet declining
- (Persistently) less use of highly energy-intensive appliances (dryer)



## Experimental design

- Randomized controlled trial with around 750 participants
- Participants are customers of a large German utility
- Receive smart meter, internet gateway and smartphone app

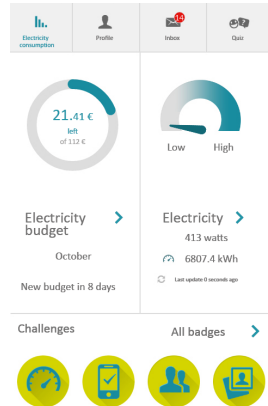
## Experimental design

- Randomized controlled trial with around 750 participants
- Participants are customers of a large German utility
- Receive smart meter, internet gateway and smartphone app
- Five experimental conditions:

	Control	T1	T2	T3	T4
Aggregated feedback	✓	✓	✓	✓	✓
Disaggregated feedback	-	✓	✓	✓	✓
Efficiency Challenges	-	-	✓	✓	✓
Monetary Incentives	-	-	✓	-	✓
Ranking	-	-	-	✓	✓

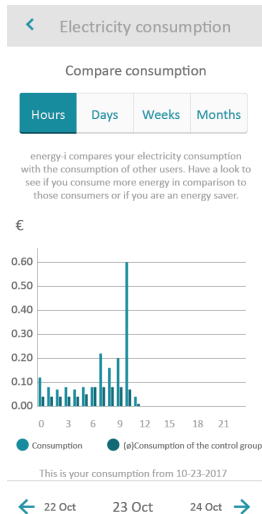
# Control condition

- Participants observe remaining part of monthly advance payments (budget)
- Observe current wattage
- Can do a energy-related quiz
- Obtain badges for filling out their profile, etc.



# Control condition

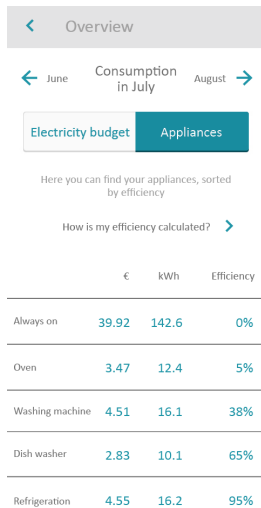
- Participants obtain aggregate electricity use feedback
- Observe total consumption (and electricity cost)
- Can compare it to other app users and their history





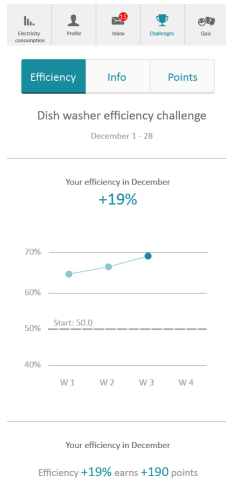
# Disaggregation condition (T1)

- Additional display of appliance-level consumptions
- Disaggregation is based on a commercial machine-learning algorithm
- Available for: refrigeration, dishwasher, washing machine, dryer, always-on (and oven)
- Calculation of efficiency scores (0: very inefficient, 100: very efficient)



# Efficiency Challenges (T2-T4)

- Participants enter monthly challenges to improve the efficiency of a certain appliance use
- Challenges start on the 1st of a month, given that at least one month of data is available
- T2: financial **incentives** (1 EUR per 1% of efficiency improvement)
- T3: display of **rank** compared to other study participants
- T4: **competition** for rank improvements (with financial reward per improved rank position)



# Data

- High-resolution smart meter data on electricity consumptions
- “Appliance use events”: use and time-of-use of appliances
- Three surveys: baseline, after 3 months, after 6 months (socio-demographics, attitudes, electricity-saving behaviors)
- Billing information: billed annual consumption
- App analytic: page views

## Timeline

- First participants installed the app in November 2016 (majority in January 2017)
- Field experiment was ended in September 2017

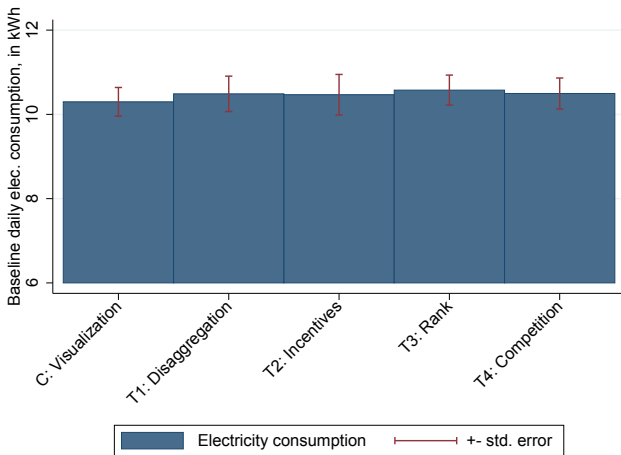
## Timeline

- First participants installed the app in November 2016 (majority in January 2017)
- Field experiment was ended in September 2017

Three phases in the experiment:

- Month 1: Disaggregation for T1–T4
- Month 2–6: Challenges for T2–T4
- Month 7+: Persistency phase

## Balancing



- F-statistic of a test for mean equality: 0.34 ( $p$ -value: 0.85)

## Empirical strategy

- Estimation of ATE, relative to visualization only
- Control for baseline electricity use (from billing data)
- Standard errors clustered at individual level

### Estimation equation:

$$Y_{it}^{norm} = \alpha Y_i^{bill} + \sum_{d=1}^4 \beta^d T_i^d + \nu_t + \epsilon_{it}$$

- $Y_{it}^{norm}$ : Electricity use of participant  $i$  in month  $t$  (normalized by control group mean)
- $Y_i^{bill}$ : Billed electricity use in baseline year
- $T_i^c$ : Treatment group indicators
- $\nu_t$ : Month fixed effects

## Effect on electricity consumption

	Short Term (M1)	
T1-T4: Joint spec.	-0.106***	
	(0.033)	
T1: Disaggregation	-0.114***	
	(0.036)	
T2: Incentives	-0.127***	
	(0.047)	
T3: Rank	-0.111***	
	(0.036)	
T4: Competition	-0.071*	
	(0.041)	
Baseline elec. use	✓	✓
Month fixed effects	✓	✓
$R^2$	0.6667	0.6681
Number of obs.	577	577
Number of participants	577	577

Notes: \*\*\*, \*\*, \* denote statistical significance at the 1%, 5%, 10% level, respectively. Standard errors are in parentheses and clustered at the individual level.



## Effect on electricity consumption

	Short Term (M1)		Medium Term (M2-6)	
T1-T4: Joint spec.	-0.106*** (0.033)		-0.050*** (0.017)	
T1: Disaggregation		-0.114*** (0.036)		-0.037* (0.022)
T2: Incentives		-0.127*** (0.047)		-0.060** (0.026)
T3: Rank		-0.111*** (0.036)		-0.070*** (0.022)
T4: Competition		-0.071* (0.041)		-0.029 (0.023)
Baseline elec. use	✓	✓	✓	✓
Month fixed effects	✓	✓	✓	✓
$R^2$	0.6667	0.6681	0.7054	0.7065
Number of obs.	577	577	3,132	3,132
Number of participants	577	577	691	691

Notes: \*\*\*, \*\*, \* denote statistical significance at the 1%, 5%, 10% level, respectively. Standard errors are in parantheses and clustered at the individual level.

## Effect on electricity consumption

	Short Term (M1)		Medium Term (M2-6)		Long Term (M7+)	
T1-T4: Joint spec.	-0.106*** (0.033)		-0.050*** (0.017)		-0.011 (0.020)	
T1: Disaggregation		-0.114*** (0.036)		-0.037* (0.022)		0.017 (0.026)
T2: Incentives		-0.127*** (0.047)		-0.060** (0.026)		-0.012 (0.026)
T3: Rank		-0.111*** (0.036)		-0.070*** (0.022)		-0.017 (0.026)
T4: Competition		-0.071* (0.041)		-0.029 (0.023)		-0.030 (0.025)
Baseline elec. use	✓	✓	✓	✓	✓	✓
Month fixed effects	✓	✓	✓	✓	✓	✓
$R^2$	0.6667	0.6681	0.7054	0.7065	0.6705	0.6718
Number of obs.	577	577	3,132	3,132	2,998	2,998
Number of participants	577	577	691	691	607	607

Notes: \*\*\*, \*\*, \* denote statistical significance at the 1%, 5%, 10% level, respectively. Standard errors are in parantheses and clustered at the individual level.

## Empirical strategy II

- Analyze ATE at appliance level
- Control on baseline consumption and number of occupants

### Estimation equation:

$$Y_{ijt}^{norm} = \alpha Y_i^{bill} + \gamma X_i + \sum_{d=1}^4 \beta^d T_i^d + \nu_t + \epsilon_{it}$$

- $Y_{ijt}^{norm}$ : Electricity use of appliance  $j$  by participant  $i$  in month  $t$  (normalized by control group)
- $Y_i^{bill}$ : Billed electricity use in baseline year
- $X_i$ : Number of occupants fixed effects
- $T_i^c$ : Treatment group indicators
- $\nu_t$ : Month fixed effects

## Effect on appliances use (appliance specific, M1)

	Always-On	Cooling	Dish-Washer	Washing	Dryer	Oven	Residual
T1: Disaggregation	-0.065 (0.073)	-0.056 (0.062)	0.004 (0.117)	0.083 (0.123)	0.012 (0.191)	-0.081 (0.176)	-0.170*** (0.060)
T2-T4: Challenges	-0.099 (0.063)	0.004 (0.053)	-0.063 (0.097)	-0.093 (0.093)	-0.199 (0.153)	-0.002 (0.150)	-0.140** (0.056)
Baseline elec. use	✓	✓	✓	✓	✓	✓	✓
Month fixed effects	✓	✓	✓	✓	✓	✓	✓
$R^2$	0.416	0.182	0.220	0.147	0.039	0.094	0.538
Number of obs.	577	577	520	567	409	577	577
Number of participants	577	577	520	567	409	577	577

Notes: \*\*\*, \*\*, \* denote statistical significance at the 1%, 5%, 10% level, respectively. Standard errors in parantheses, clustered at the individual level.

## Effect on appliances use (appliance specific, M2-6)

	Always-On	Cooling	Dish-Washer	Washing	Dryer	Oven	Residual
T1: Disaggregation	0.053 (0.065)	-0.003 (0.062)	-0.149 (0.119)	-0.037 (0.087)	-0.495** (0.218)	-0.059 (0.211)	-0.068** (0.031)
T2-T4: Challenges	-0.027 (0.053)	-0.013 (0.042)	-0.150 (0.095)	-0.065 (0.070)	-0.541*** (0.187)	-0.005 (0.185)	-0.072*** (0.028)
Baseline elec. use	✓	✓	✓	✓	✓	✓	✓
Month fixed effects	✓	✓	✓	✓	✓	✓	✓
$R^2$	0.379	0.146	0.177	0.133	0.167	0.101	0.547
Number of obs.	3,132	3,131	2,835	3,073	2,205	3,132	3,132
Number of participants	691	691	626	677	492	691	691

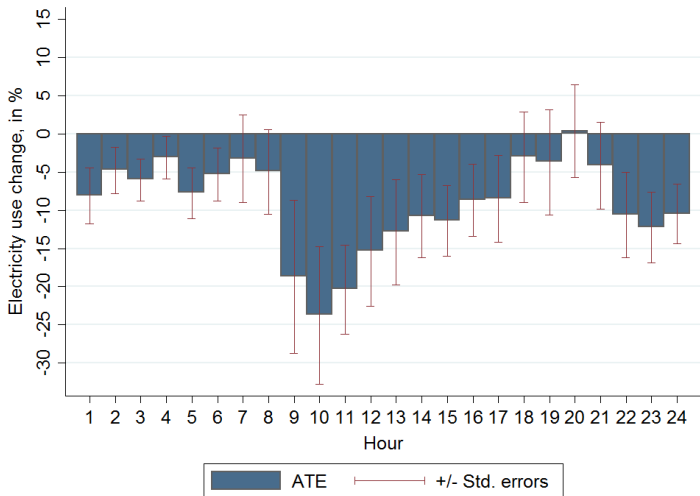
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## Effect on appliances use (appliance specific, M7+)

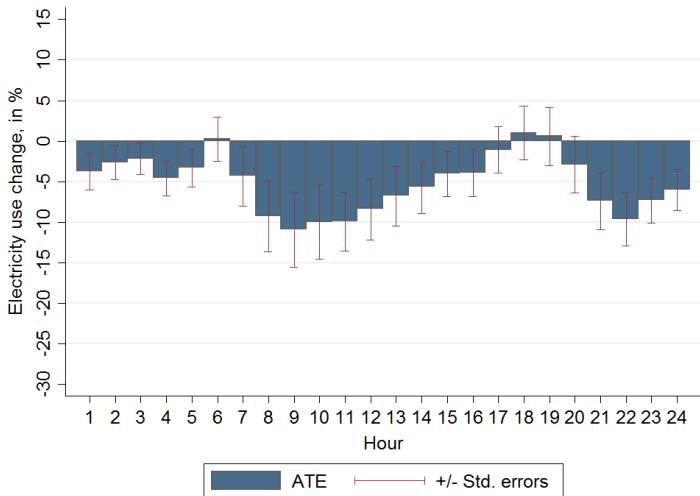
	Always-On	Cooling	Dish-Washer	Washing	Dryer	Oven	Residual
T1: Disaggregation	0.117* (0.068)	-0.030 (0.049)	-0.162 (0.113)	-0.099 (0.080)	-0.249 (0.224)	-0.044 (0.157)	0.016 (0.032)
T2-T4: Challenges	0.046 (0.055)	-0.029 (0.038)	-0.196** (0.089)	-0.106 (0.065)	-0.422** (0.168)	0.079 (0.140)	-0.032 (0.026)
Baseline elec. use	✓	✓	✓	✓	✓	✓	✓
Month fixed effects	✓	✓	✓	✓	✓	✓	✓
$R^2$	0.350	0.066	0.174	0.134	0.173	0.122	0.544
Number of obs.	2,638	2,638	2,401	2,588	1,876	2,638	2,638
Number of participants	604	604	551	595	430	604	604

Notes: \*\*\*, \*\*, \* denote statistical significance at the 1%, 5%, 10% level, respectively. Standard errors in parantheses, clustered at the individual level.

## Disag. effect by hour of day (M1)

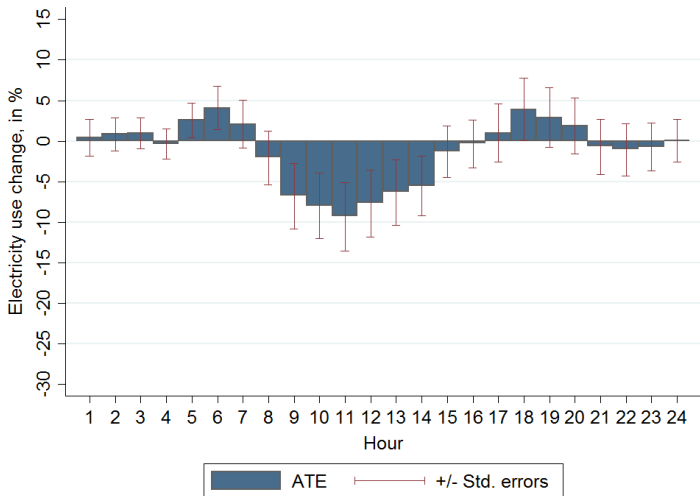


## Disag. effect by hour of day (M2-6)





## Disag. effect by hour of day (M7+)



## Summary

- Disaggregation-based services achieve large short- and medium-run electricity savings ( $\approx 5\text{-}10\%$ ) beyond visualization only
- Mechanism: Reduced use of highly electricity-using appliances (persistent over time)
- Efficiency challenges improve the effectiveness only slightly, monetary incentives are not more effective than social information

Thank you for your attention. Any comments?