



## Using Time Use Data to Model Residential Electricity Load Profiles

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WORKSHOP ON ELECTRICITY DEMAND: NEW MODELLING PERSPECTIVES

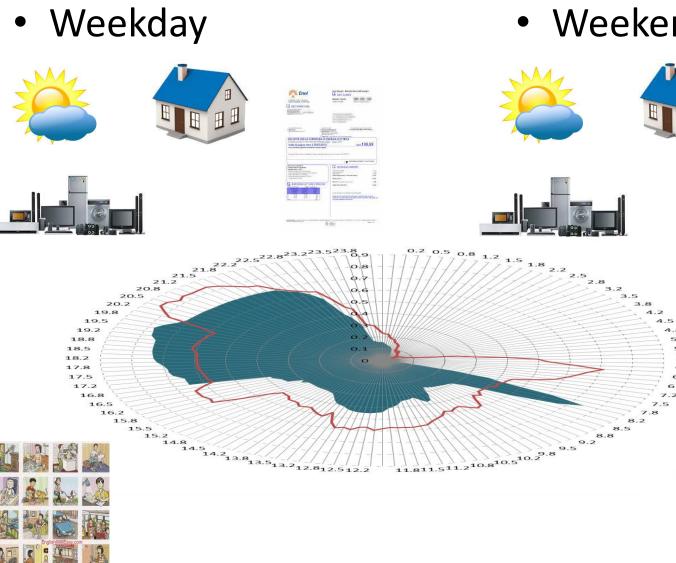
Université Paris-Dauphine 6 March 2017



### Starting point / problem definition

- Peaks in electricity demand bring about significantly negative environmental and economic impacts
- In the UK, the residential sector is responsible for about one third of overall electricity demand and up to 40% of peak demand
- In the future the peak problem will worsen due to the integration of intermittent renewables in the supply mix as well as electric vehicles and electric heat pumps
- Little is known about residential peak demand and what levels of flexibility might be available







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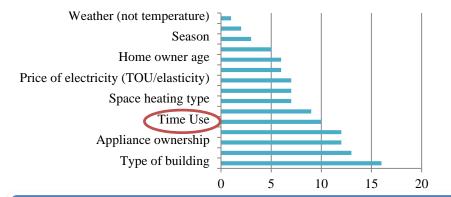


### Outline

- Deriving load profiles from time use data
- Deriving occupancy for 15 European countries
- Applications in Spain and UK
- Implications for price elasticity



# State-of-the-art in residential electricity demand studies



-Building, occupants' income, appliance ownership and bill-related price of electricity are some of the most used data in models for residential electricity demand

-These variables so far been able to explain less than 40% of variation (DECC, 2013)

-They are not able to explain in-day load profiles

#### The timing of people's activities plays a vital role in explaining residential load profiles

	Number of dwellings (simulation)	Sample size (from time use surveys)	Country	Duration	Period	Approach	Time resolution (in minutes)
Capasso et al (1994)	95 (4 buildings)	40000	Italy	1 year	1/6/1988 - 31/5/1989	Montecarlo analysis	15
Duffy et al (2010)	5	-	Ireland	6 months	1/7/2009 - 31/12/2009	Markov chain compared with measured data	30
Richardson et al (2008)	50	9991	UK	1 year	2000	Markov chain compared with measured data	10
López-Rodríguez et al (2013)	-	9541	Spain	1 year	2009-2010	Estimating occupancy variances	10
Richardson et al (2010)	22	9991	UK	1 year	2000	Markov chain compared with measured data	10
Stokes et al (2004)	100	-	UK	1 year	1/3/1996 - 30/4/1997	Stochastic approach to model residential light demand	1
Torriti (2012a)	-	73215	EU15	1 year	1991-1006	Estimating occupancy variances	10
Widén et al (2009a)	217	3980	Sweden	1 year	1996 and 2007	Markov chain to model residential hot water demand	5
Widén et al (2009b)	14	3980	Sweden	1 year	1996 and 2007	Markov chain to model residential light demand	10
Widén and Wäckelgård (2010)	169	3980	Sweden	1 year	1996 and 2007	Markov chain compared with measured data	1
Wilke et al (2013)	20	15441	France	1 year	1998-1999	Markov chain to calculate probabilities of different activities	10



### Time use data

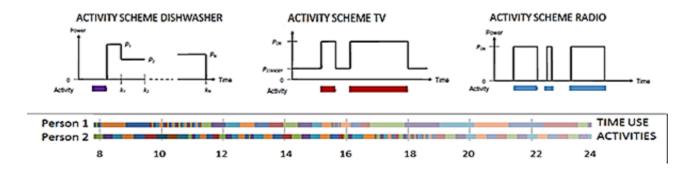
### Selfrecorded diary

• 10 minute granularity

D	iary/	Startin	Endin	Main activity	Parallel activity	Who with:			Where/m	
		g	g			Alone	Spous	Smal	Othe	ode of
р	erson						e	I.	r	tranport
id	I	Time	Time					child	pers.	
А	A23	04:00	07:20	Sleep						At home
А	A23	07:20	07:50	Shower						At home
А	A23	7:50	08:30	Had breakfast	Read newspaper			Ch		At home
А	A23	08:30	08:40	Walked to bus		А				By foot
A	A23	08:40	09:00	Bus to job					ОР	By bus

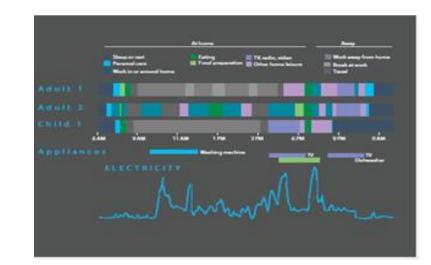
		Work and			Sleep and			TV and	
Country	StartTime	study	Travel to/from	Household work	other	Eating	Freetime	video	Unspecified time
			work/study		personal care				
Belgium	04:00	1.04	0.07	0.16	97.16	0.15	1.01	0.17	0.24
Belgium	04:10	1.09	0.09	0.28	97.14	0.18	0.85	0.14	0.23
Belgium	04:20	1.09	0.15	0.18	96.94	0.4	0.81	0.17	0.25
Belgium	04:30	1.13	0.35	0.23	96.51	0.27	1.09	0.17	0.27
Belgium	04:40	1.23	0.34	0.36	96.46	0.2	0.97	0.15	0.29
Belgium	04:50	1.26	0.35	0.44	95.81	0.49	1.16	0.18	0.31
Belgium	05:00	1.53	0.34	0.61	94.76	0.49	1.78	0.21	0.27
Belgium	05:10	1.6	0.47	0.68	94.82	0.61	1.34	0.21	0.27
Belgium	05:20	1.71	0.64	0.61	94.54	0.65	1.25	0.24	0.36
Belgium	05:30	1.83	0.95	0.7	93.31	0.77	1.84	0.22	0.37
Belgium	05:40	1.94	1.26	0.99	92.77	0.74	1.74	0.24	0.3
Belgium	05:50	2.31	1.22	1.08	91.76	0.98	2.09	0.21	0.36
Belgium	06:00	3.08	1.06	1.39	88.08	1	4.81	0.23	0.34

# Time use data and load profiles



Activity schemes can enable to link time use activities with appliance and electricity use

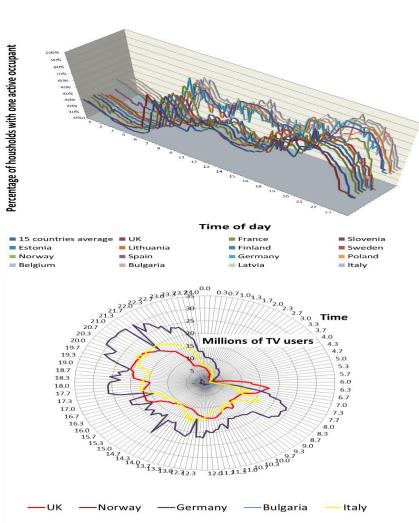
EAK



## Deriving occupancy for 15 European countries



- -Harmonised European Time Use Survey (HETUS) database consists of 220,464 residential users across 15 countries
- -Active occupancy: how much occupancy varies within peak periods



### Activities at home of single households between 20h10 and 20h20

Country	Start	End	Work	Travel	Household	Sleep	Eating	Free	TV	Unspe
	Time	Time	and	to/from	work (%)	and	(%)	time (%)	and	cified
			study	(%)		other			video	time
			(%)			(%)			(%)	(%)
Belgium	20:10	20:20	4.5	0.63	15.37	4.58	13.72	22.1	36.76	2.35
Bulgaria	20:10	20:20	3.66	0.75	16.08	3.75	26.53	10.11	38.84	0.28
Finland	20:10	20:20	6.86	0.62	16.87	7.4	6.95	26.76	32.52	2.02
France	20:10	20:20	4.49	1.05	15.88	4.29	36.71	10.34	24.58	2.65
Estonia	20:10	20:20	7.08	1.55	19.86	5.56	9.29	20.08	35.86	0.73
Germany	20:10	20:20	4.49	0.79	12.32	3.22	9.83	29.63	38.58	1.14
Italy	20:10	20:20	4.1	1.44	18.45	4.18	38.97	16.46	15.06	1.34
Latvia	20:10	20:20	8.18	2.25	15.12	4.94	13.16	16.22	39.63	0.51
Lithuania	20:10	20:20	7.76	1.13	17.2	6.91	11.45	13.96	40.9	0.68
Norway	20:10	20:20	6.89	0.61	18.86	2.61	7.86	39.08	23.69	0.38
Spain	20:10	20:20	11.37	2.66	25.03	4.92	8.68	34.16	12.72	0.46
Poland	20:10	20:20	6.22	0.81	15.48	7.99	10.54	17.38	40.74	0.86
Sweden	20:10	20:20	6.88	0.65	16.69	3.29	8.8	29.22	33.58	0.89
Slovenia	20:10	20:20	6.34	0.75	15.08	8.48	8.85	21.07	39.08	0.35
UK	20:10	20:20	5.68	0.9	15.18	4.2	9.16	26.44	37.29	1.15



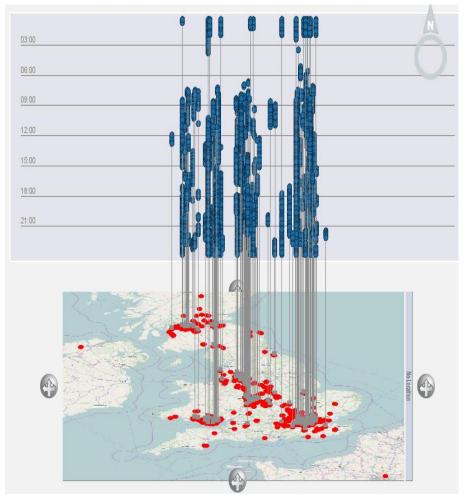
- High peak variance→smart appliances
- Low peak variance→manual and incentive-based DSM programmes
- Low non-peak variance → DDSC
- High baseline variance → *ToU*

Country	β	$\mu_{MP} \ \mu_{EP}$	$egin{aligned} (eta-\mu_{MP})\ (eta-\mu_{EP}) \end{aligned}$
Belgium	<b>0.193</b> (0.027)	0.05	0.142 0.159
Bulgaria	0.194	0.048	0.146
	(0.071)	0.011	0.183
Finland	0.130	0.024	0.106
	(0.056)	0.010	0.120
Estonia	0.127 (0.028)	0.008	0.119 0.106
Germany	0.113	0.043	0.070
	(0.015)	0.022	0.091
Italy	0.124	0.049	0.075
	(0.023)	0.024	0.100
Latvia	0.128	0.011	0.117
	(0.027)	0.024	0.104
Lithuania	0.131 (0.025)	0.009	0.122 0.113
Norway	0.130	0.057	0.073
	(0.026)	0.012	0.118
Spain	0.192 (0.031)	0.064	0.128 0.135
Poland	0.101	0.051	0.060
	(0.019)	0.012	0.089
Sweden	0.126	0.054	0.072
	(0.025)	0.014	0.112
Slovenia	0.144	0.041	0.103
	(0.023)	0.025	0.119
United Kingdom	(0.023)	0.091 0.020	0.074 0.145



# Applications in UK and Spain: Knowing where and when

#### Computer use-UK



#### TV use-Spain



### Average TV electricity consumption in Spain (MWh)

		Morning Peak	Evening Peak
Waaladaara	Minimum	7,93	82,35
Weekdays	Maximum	17,45	181,18
Weekends	Minimum	17,30	104,13
	Maximum	38,06	229,08



### UK Trajectory time use dataset



- 500 respondents
- with GPS devices for 3 days
- collecting 10 minute interval data (May-November 2011)
- + diary and questionnaire information on what people were doing at any given time of the day
- The Trajectory dataset allows temporal analysis to be combined with spatial analysis of the data

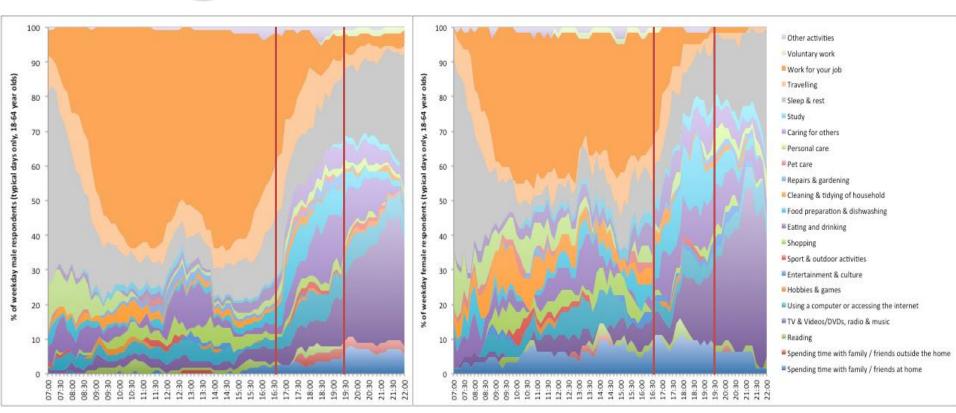


### UK data - gender











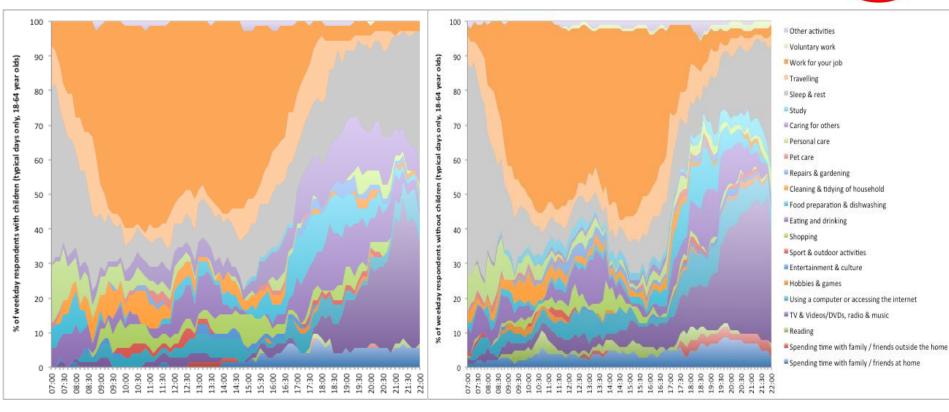
### UK data: with or without children

#### With Children



#### Without children



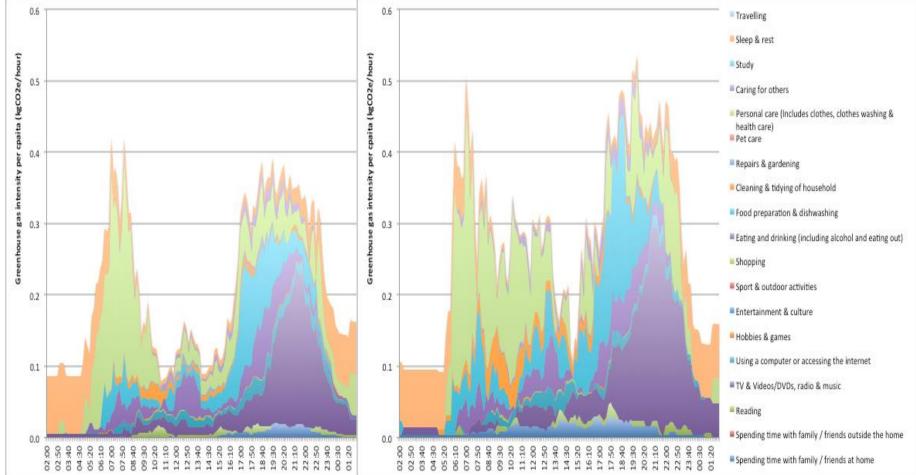




### UK data: Greenhouse gas emissions









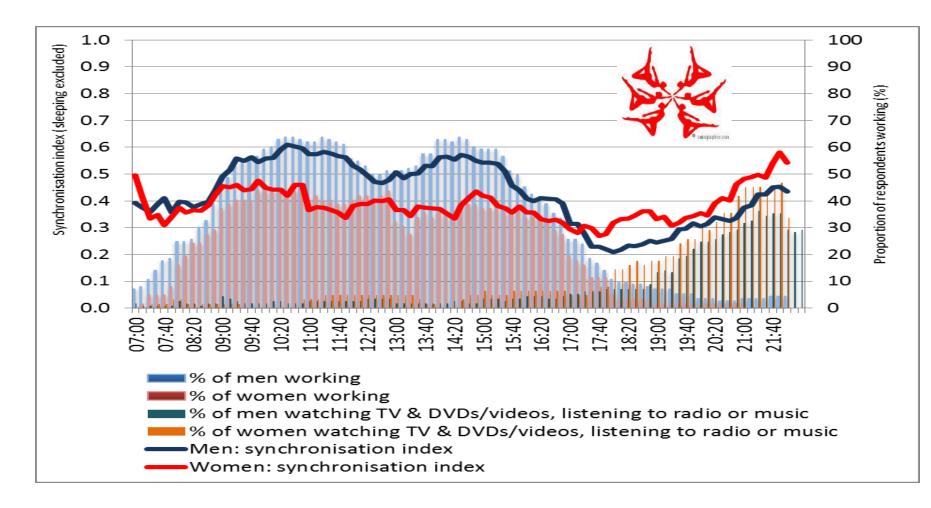
### Flexibility index



- (i) higher synchronicity index implies higher societal constraints (i.e. lower flexibility)
- (ii) A higher number of activities distributed through the day makes it more difficult to move activities to different times of the day (i.e. lower flexibility).
- (iii) a higher number of shared activities with others implies that there is higher simultaneity of loads and within-thehousehold synchronisation, making it more difficult to move shared activities in time (i.e. lower flexibility)
- (iv) higher spatial mobility at a given time leads and lower active occupancy for an extended period of time imply that there is more time to do things (i.e. higher flexibility)



### 1: Synchronisation: men and women

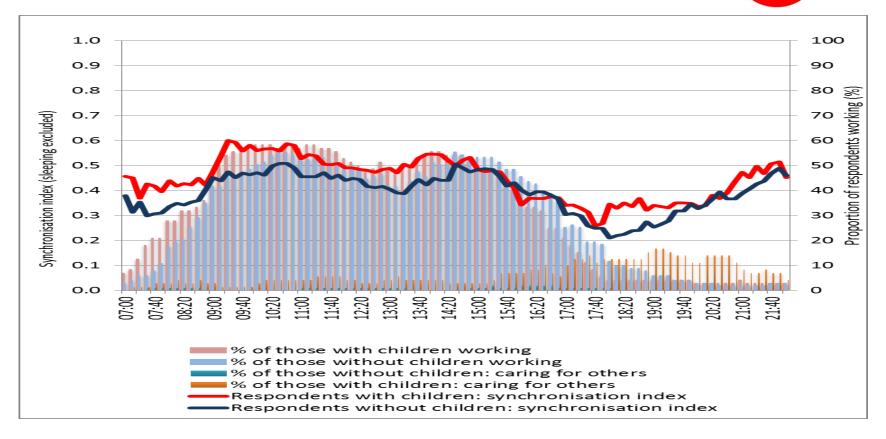




# 1: Synchronisation: respondents with children compared to those without children









### 2: Variation and activities over time

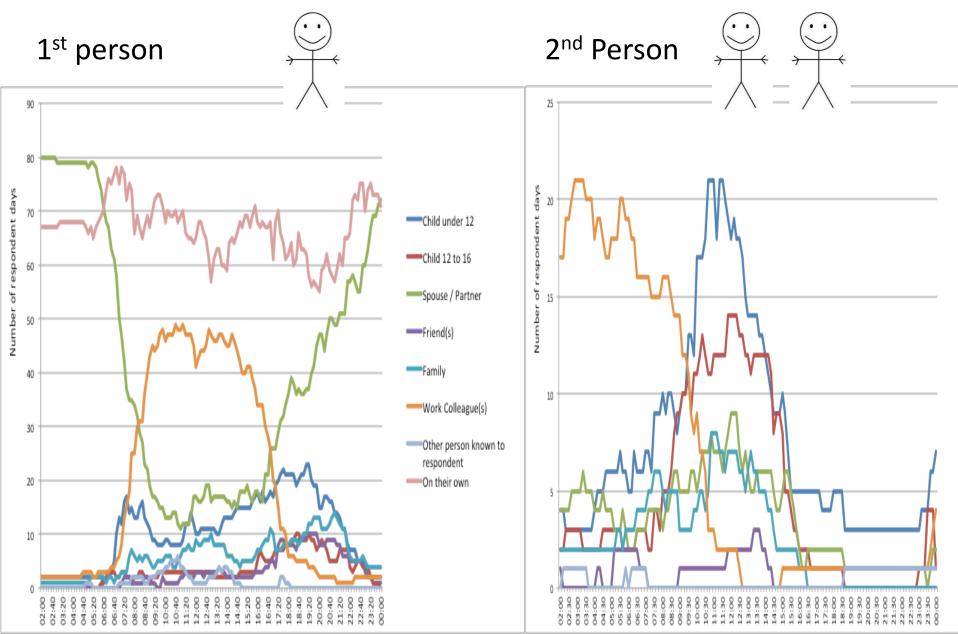
• Variation index = number of activities performed over a given time period (from a total of 38 activity codes) and changes in location

Demographic group	2am - 2am	Morning peak: 7am - 10am	Evening peak: 4pm - 10pm	Average % of time, 2am – 2am: working	Average % of time, 4pm – 10pm: food preparation, cooking & washing up
All males	8.1	3.6	4.8	23.1%	5.6%
All females	9.6	4.0	5.3	14.5%	8.1%
Males who worked	8.4	3.9	5.2	31.9%	4.2%
Females who worked	9.4	4.3	5.8	29.1%	10.3%

N.B. Respondents of working age / typical days only



### 3: Who respondents were with (weekdays)





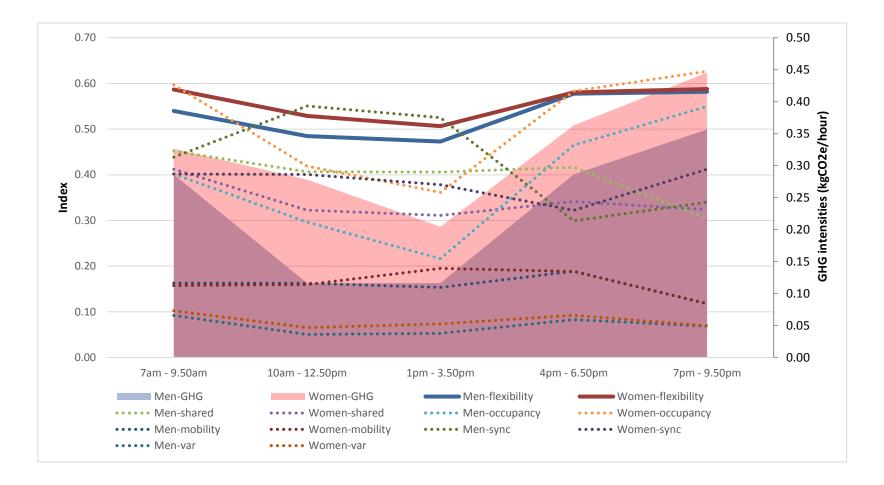
### 4: Space and occupancy

#### Spatial mobility and active occupancy

1. Spatial mobility	7.00am – 9.50am	10am – 12.50am	1pm – 3.50pm	4pm – 6.50pm	7pm – 9.50pm
All males	0.16	0.16	0.15	0.19	0.12
All females	0.16	0.16	0.20	0.19	0.12
All respondents with children	0.18	0.19	0.16	0.20	0.11
All respondents without children	0.15	0.15	0.18	0.18	0.12
2. Active home occupancy	7.00am – 9.50am	10am – 12.50am	1pm – 3.50pm	4pm – 6.50pm	7pm – 9.50pm
All males	0.40	0.30	0.22	0.46	0.55
All females	0.60	0.42	0.36	0.58	0.63
All respondents with children	0.56	0.31	0.26	0.52	0.60
All respondents without children	0.42	0.36	0.28	0.51	0.56

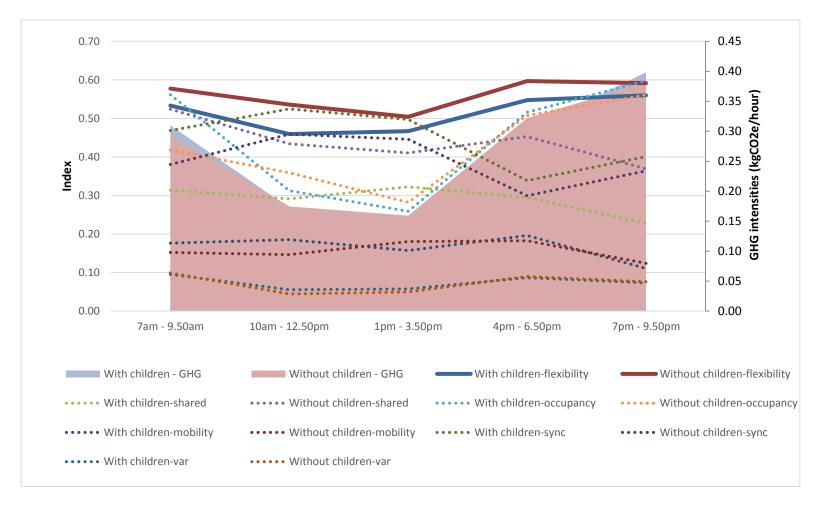


### Flexibility index: men and women





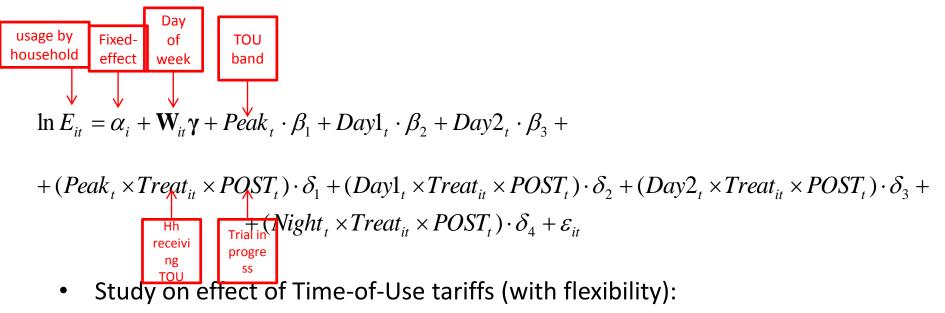
### Flexibility index: with and without children





### Implications for price elasticity

• Study on effect of Time-of-Use tariffs (without flexibility):



 $\begin{aligned} \ln E_{it} &= \alpha_{i} + \mathbf{W}_{it} \gamma + Peak_{t} \cdot \beta_{1} + Day1_{t} \cdot \beta_{2} + Day2_{t} \cdot \beta_{3} + \\ &+ (Peak_{t} \times Treat_{it} \times POST_{t} \times Flex_{t}) \cdot \delta_{1} + (Day1_{t} \times Treat_{it} \times POST_{t} \times Flex_{t}) \cdot \delta_{2} + (Day2_{t} \times Treat_{it} \times POST_{t} \times Flex_{t}) \cdot \delta_{3} + \\ &+ (Night_{t} \times Treat_{it} \times POST_{t} \times Flex_{t}) \cdot \delta_{4} + \varepsilon_{it} \end{aligned}$ 



## **Choice Experiment**

- Simple web-based choice experiment to elicit preferences for fixed tariffs and two dynamic tariffs (TOU and CPP)
- The price attribute was framed as an electricity bill discount (i.e. a WTA format) to switch to the dynamic tariff
- Respondents were presented with four labelled choice cards
- Respondents were randomly divided into two sub-samples, with environmental and system benefits information presented to only one

Tariff Type	Fixed	Time of Use (TOU)	Critical Peak Pricing (CPP)
Description	*Price stays the same throughout the day.	*Cost: Rate is 50% higher than your current fixed rate 6 hours of the day, every weekday, from 2pm until 8pm, during daily high demand. *Benefit: Rate is 25% lower than your current fixed rate all other times.	*Cost: On 10 weekdays selected by the electric company prices will raise 8x from your current fixed rate for 6 hours, from 2pm to 8pm, during emergency conditions. Your electric company notifies you one day in advance. *Benefit: Rate is 25% lower than your current fixed rate all other times that day and all other days in the year.
Environmental and Grid Benefits	*None	*Less water and air pollution. *Aid the expansion of renewable energy. *Increased electricity reliability. *Slow the rate of electricity price increases.	*Less water and air pollution. *Aid the expansion of renewable energy. *Increased electricity reliability. *Slow the rate of electricity price increases.
Graphic	Fixed Rate (\$/kilowatt-hour)	Fixed vs. TOU (\$/kilowatt-hour)       \$0.15       \$0.15       \$0.15       \$0.75       \$0.075       \$0.075       \$0.075       \$0.075       \$0.075       \$0.10       \$0.15       \$0.075       \$0.075       \$0.075       \$0.075       \$0.10       \$0.075       \$0.075       \$0.075       \$0.075       \$0.075       \$0.075       \$0.10       \$0.075 <t< th=""><th>Fixed vs. CPP (\$/kilowatt-hour)</th></t<>	Fixed vs. CPP (\$/kilowatt-hour)
Required Behavior Change to get Savings	*None - it's your current plan.	Sustained, moderate changes during daily high priced times: *All regions: Shift all listed appliances. *U.S.: Adjust thermostat up by 2F (1C) from 75F (25C) during the summer. *Europe: If you use electric heating, adjust your thermostat down by 2F (1C) from 68F (20C) during the winter. Use stand-alone electric room heaters at their lowest setting.	Oneoff, significant changes during 10 days' high priced times: *All regions: Shift all listed appliances. *U.S.: Adjust thermostat up by 5F (2.5C) from 75F (25C) during the summer. Turn off window and room air conditioning units, and all but essential lighting. *Europe: If you use electric heating, adjust your thermostat down by 5F (2.5C) from 68F (20C) during the winter. Turn off stand-alone electric room heaters. Turn off all but essential lighting. Restrict use of electric cooking appliances by 50%.
Potential Bill Increase with No Behavior Change	0%	0% to 5% \$0 to \$5.00 per month	0% to 5% \$0 to \$5.00 per month
Potential Bill Savings with Behavior Change Note: the last 2 columns in this row change with each selection.	0%	10% Approximately \$10.00 per month	5% Approximately \$5.00 per month
Please Select One	Choice 1	Choice 2	Choice 3



### Information collected

- socioeconomic information
- electricity usage
- use of appliances
- heating, and cooling
- attitudes toward personal energy consumption and policy goals
- tariff choice motivations
- attitudes towards technologies and services

### Model

- Conditional and mixed logit model
- A likelihood ratio shows that the mixed logit model provides a better fit for the data at the highest levels of significance



#### Model Results with Customer Attribute Interactions

	Coefficient	Std. Error	MWTA <sup>a</sup>	Std. Error <sup>b</sup>
DISCOUNT	0.163***	0.020		
TOU <sup>c</sup>	-1.993**	0.830	12.22%	4.91%
E&SxTOU	1.599***	0.622	-9.81%	3.87%
MALEXTOU	-1.779***	0.627	10.91%	3.91%
HIBILLXTOU	1.255**	0.619	-7.70%	3.82%
STUDENTxTOU	-0.056	0.629	0.34%	3.86%
EASYxTOU	2.848***	0.657	-17.47%	4.19%
CPP <sup>c</sup>	-3.009***	1.039	18.45%	6.20%
E&SxCPP	2.086***	0.788	-12.80%	4.87%
MALEXCPP	-1.437*	0.790	8.81%	4.88%
HIBILLxCPP	-0.390	0.793	2.39%	4.86%
STUDENTxCPP	-1.728**	0.804	10.60%	4.97%
EASYxCPP	1.981**	0.802	-12.15%	5.01%
	Standard Deviations of Ra	ndom Coeffs.		
ΤΟυ	2.776***	0.381		
СРР	3.365***	0.535		
Df			13	
Replications			1000	
Observations			1920	
Log likelihood			-438.380	
$LR \chi^2$		SDs (2)	205.56***	



REDPeAk (Residential Electricity Demand: Peaks, Sequences of Activities and Markov chains) DEePRED (Distributional Effects of Dynamic Pricing for Responsive Electricity Demand)

The Association for Decentralised Energy



Bringing Energy Together









Department for Business, Energy & Industrial Strategy





# Bloomberg









### REDPeAk: recruiting now

Post-Doc Research Assistant:

https://jobs.reading.ac.uk/displayjob.aspx?jobid =469

PhD Studentship:

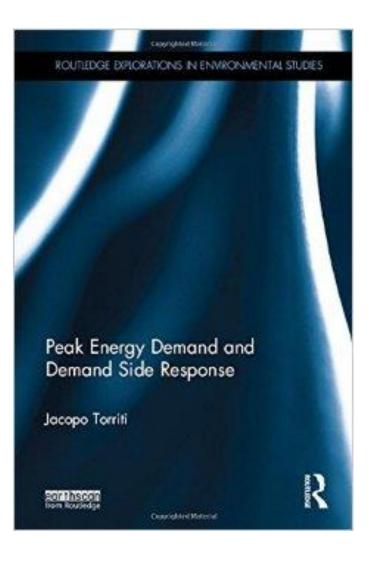
https://www.findaphd.com/search/ProjectDetail s.aspx?PJID=83869&LID=3959



### References

- Buryk, S., Mead, D., Mourato, S. and Torriti, J. (2015) Investigating preferences for dynamic electricity tariffs: the effect of environmental and system benefit disclosure. *Energy Policy*, 80. pp. 190-195.
- Torriti, J., Hanna, R., Anderson, B., Yeboah, G. and Druckman, A. (2015) Peak residential electricity demand and social practices: Deriving flexibility and greenhouse gas intensities from time use and locational data. *Indoor and Built Environment*, 24, 891-912.
- Torriti, J. (2014) A review of time use models of residential electricity demand. *Renewable and Sustainable Energy Reviews*, 37. pp. 265-272.
- Santiago, I., Lopez-Rodriguez, M. A., Trillo-Montero, D., Torriti, J. and Moreno-Munoz, A. (2014) Activities related with electricity consumption in the Spanish residential sector: variations between days of the week, Autonomous Communities and size of towns. *Energy and Buildings*, 79. pp. 84-97.
- Torriti, J. (2012) Demand side management for the European Supergrid: occupancy variances of European single-person households. Energy Policy, 44. pp. 199-206.





Peak Energy Demand and Demand Side Response (Routledge), pp. 172

https://www.routledge.com/products/9 781138016255

