Title

Domestic energy prepayment and fuel poverty: Induced self-selection influencing the welfare of fuel-poor households

Sotirios Thanos, Maria Kamargianni, Ian Hamilton
UCL Energy Institute, The Bartlett, London

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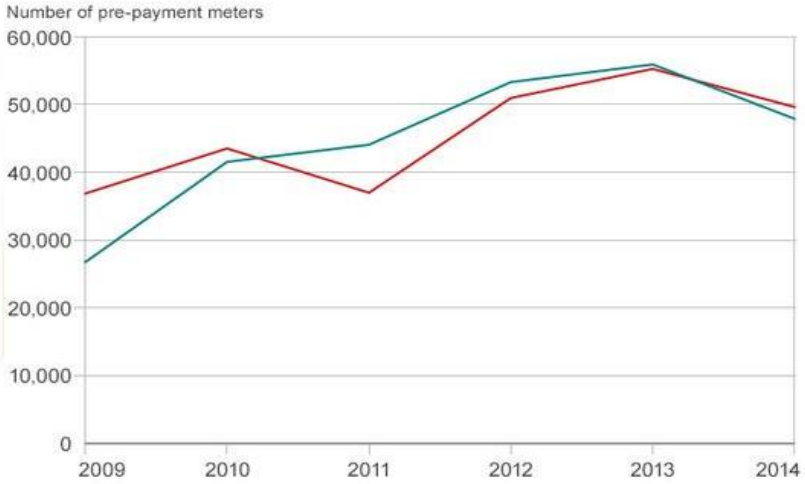
Ofgem to investigate 'forcibly installed' pre-pay meters

26 May 2015 | UK

Pre-payment meters installed under court order due to debt
England, Wales and Scotland



Source: BBC Radio 5 Live Ofgem FOI request

BBC

More than half a million pre-payment energy meters have been forcibly installed in people's homes over the last six years

Energy suppliers can gain a court order to install a pre-pay meter when customers run up debt.

Industry body Energy UK said pre-paying helped some people manage a budget.

But Citizens Advice said pre-pay customers got a "raw deal", paying £80 a year more on average than direct debit customers.

Thanos and Dunse (2012) found £91/year more for prepayment

'People become trapped'

Ofgem

Energy watchdog Ofgem said it would be "looking into reasons behind the increase in the number of PPMs installed for non-payment of debt on a warrant visit".
"Pre-payment meter customers can't take advantage of the competitive energy market," she added. "Many people become trapped on them and can't get a better deal."

Energy UK

Energy UK, the umbrella body for energy suppliers, said suppliers only installed pre-payment meters with a court warrant "as a last resort to help customers manage their debt".

Chief executive Lawrence Slade said they were not always the most expensive form of payment and that prices had come down over recent years.

He said the meters could help people manage their energy use, saying: "People will often ask for a pre-payment meter voluntarily because they like the fact it gives them more control over their consumption."

Objectives

- Investigate the factors affecting Payment-Method selection
  - Initial results only for domestic heating in this presentation
- Specify latent class discrete choice model (LCM) that identifies unobservable subgroups within the data
  - Allowing better understanding:
    - the impact of Payment-Method to patterns of multiple risks, fuel poverty being one of those
    - the antecedents and consequences of complex behaviours
  - Estimate price, quantity, socioeconomic, and housing characteristic effects on Payment-Method selection
- Provide policy recommendations tailored to target the subgroups that are affected most

Latent Class Models

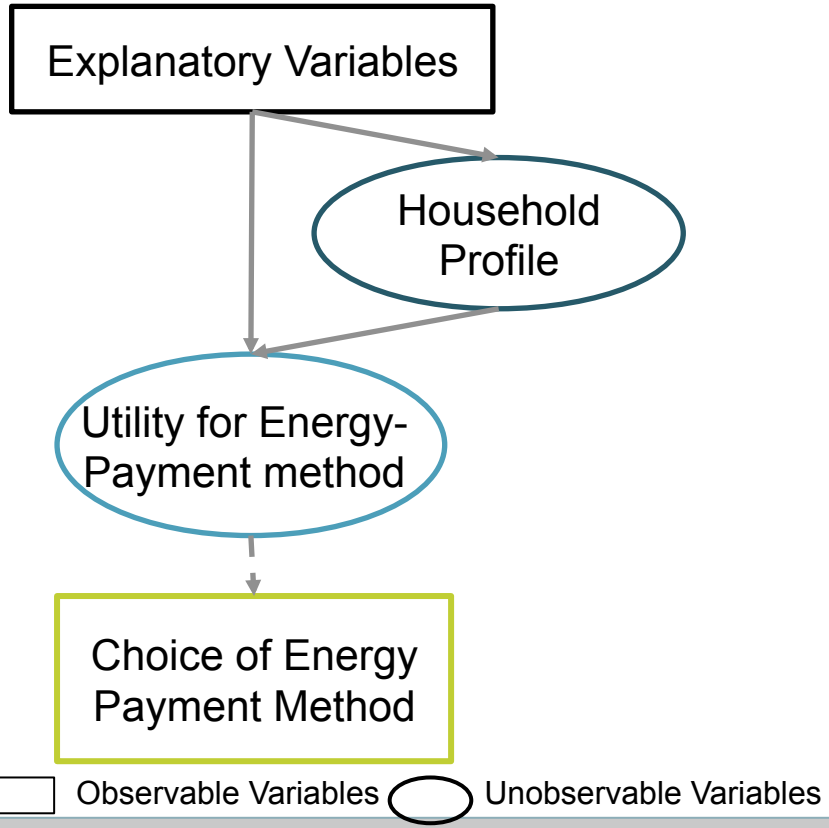
- Latent class analysis assumes that individuals differ in their behaviours due to unobservable latent traits.
- Models seek to determine subpopulations, or latent classes, within a general population in the absence of explicit group identifiers.
- LCM groups participants into classes based on probabilities - stochastic process –
  - rather than deterministic in traditional cluster analysis.
- The respondent is assigned to the class for which it has the highest probability of belonging to.

LCMs are appropriate for our analysis as the hypothesis is that:

- different household profiles exist,
- these profiles are not directly observable, and
- each profile has distinct energy-payment behaviour.

Model Specification

- Latent Class - Multinomial Logistic Regression



$$P(y_{ih} = m \mid x, z_i) = \pi_{m|h,x,z_i} = \frac{\exp(\eta^h_{m|x,z_i})}{\sum_{m'} \exp(\eta^h_{m'|x,z_i})}$$

i = *individual*
h = subset
y_{ih} = choice set
m = *particular category of* y_{ih}
x, z_i = explanatory variables

$\pi_{m|h,x,z_i}$ = probability of giving response m given x and z_i

$\eta^h_{m|x,z_i}$ = term giving the multinomial logistic regression

Data Sources

- 2011 Energy Follow-Up Survey (EFUS), a cross-sectional sub-sample survey of households in the English Housing Survey (EHS) 2010-2011
- Carried out by the Building Research Establishment on behalf of the UK Dept. of Energy and Climate Change
- The respondent is assigned to the class for which it has the highest probability of belonging to.

Questionnaire

- A self-completion survey about dwelling and heating practices.
- Gas and electricity meter readings obtained in a subsample of homes
- All households in the survey had also participated in the English Housing Survey (EHS) which collects detailed information about the English building stock.

Sample size => EHS 2011=2616 households

EHS – EFUS – Missing data = 1336 households

Model Components

Choice Set	Percent
1: Direct Debit	61.55
2: Standard Credit	19.76
3: Prepayment Meter	12.13
4: Other (Communal heating, Oil)	6.59

Covariates (Basis for Classes)
Rural vs. Non-rural areas
Fuel poor* vs. Non-fuel poor

**Fuel poor if household spends more than 10% of income on fuel*

Explanatory Variables
Household size (cont.)
Annual household income (£ | cont.)
Aver. age of partners (cont.)
Length of residence (years | cont.)
Tenure (Dummy: Rental, RSL, Local Authority)
Price implied (cont.)
KWH heating from main fuel (cont.)
House Type (Dummy: Flat, Terrace, Detached)
Energy supplier change in the last semester (Dummy)
London (Dummy)

Defining the Number of Classes

Goodness-of-fit:

$$\bar{\rho}^2 = 1 - \frac{L^* - k}{L^0} \qquad AIC = -2\ln L^* + 2k \qquad BIC = -2L^* + \ln(N)k$$

	LL	AIC	BIC	ρ^2
Model with 1 class	-1150	2390	**2624**	0.154
Model with 2 classes	-1019	2218	2685	0.457
Model with 3 classes	-961	**2177**	2878	**0.718**

Model with 3 classes is preferred

Predominant Characteristics of Classes

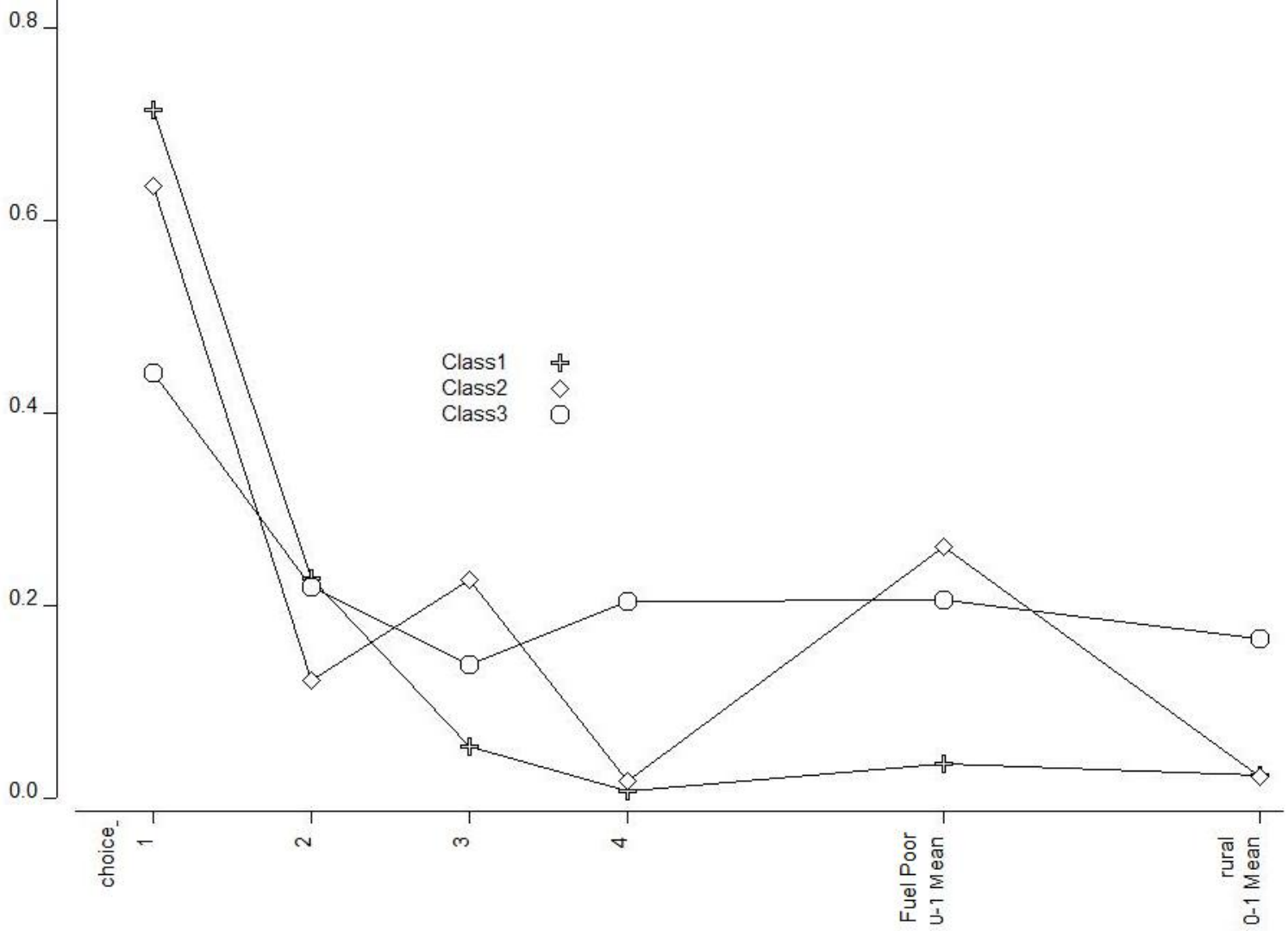
Class 1

Class 2

Class 3

Model for Classes	Class1	z-value	Class2	z-value	Class3	z-value	Wald	p-value
Intercept	0.508	5.466	-0.217	-2.162	-0.291	-2.759	29.875	3.30E-07
Fuel poverty	-1.386	-4.853	0.890	4.743	0.496	2.462	26.939	1.40E-06
Rural	-0.610	-1.377	-0.794	-1.702	1.404	6.117	37.624	6.80E-09

Classes and Choices



Result Highlights

Predictors	Choice	Class1: Non-fuel poor/urban	z-value	Class2: Fuel poor/urban	z-value	Class3: Fuel poor/Rural	z-value
Household Size	1: DD	-5.2216	-3.1828	0.6681	0.9112	0.0881	0.4254
	2: SC	-4.89	-2.975	0.9053	0.9871	-0.411	-1.3383
	3: Pre	9.3881	2.3426	2.9446	3.0672	0.2924	1.5245
	4:Other	0.7235	0.2249	-4.518	-2.1614	0.0306	0.1549
Income	1: DD	0.0004	2.9181	0.0007	3.4672	0.0001	3.9317
	2: SC	0.0004	2.9808	-0.0009	-2.7261	-0.0001	-2.641
	3: Pre	-0.0006	-1.9395	-0.0008	-2.9169	-0.00001	-0.2366
	4:Other	-0.0002	-0.7514	0.0009	3.7141	0.00001	1.2579
Implied Price	1: DD	96.7326	2.4604	31.5089	2.3235	-62.774	-5.224
	2: SC	97.1593	2.4717	-60.1519	-2.2048	14.6724	3.2172
	3: Pre	-287.87	-2.5573	26.7952	2.3804	11.9838	2.5995
	4:Other	93.9785	1.8136	1.8478	0.1046	36.1178	6.1808
Rented House	1: DD	9.2487	1.7936	0.9526	0.4076	-1.9584	-2.3584
	2: SC	10.744	2.0871	-22.8153	-2.9582	0.0384	0.0587
	3: Pre	-22.2451	-1.491	17.2051	3.1453	2.0948	3.5669
	4:Other	2.2523	0.3486	4.6576	1.1253	-0.1748	-0.3006

Additional Findings

- KWh
  - Counterintuitively, high fuel consumption increases prepayment in urban areas
- Age
  - Urban fuel-poor of lower age tend to prepay, in contrast to rural fuel-poor of higher age who tend to prepay
- House type
  - Flats and terrace houses tend to prepayment more than semis and detached
- Energy Supplier change
  - Recent supplier change has no significant effect for fuel “rich”
  - Recent supplier change has significant effects for the fuel poor, which are negative only for standard credit payment
- Length of Residence
  - No significant effect for fuel “rich”, it reduces prepayment in rural areas and increases DD in urban.
- London
  - Increased prepayments for urban fuel “rich” and reduced prepayment for urban fuel poor

Conclusions

- Prepayment in its current form distorts market conditions
  - Non-fuel poor move away from prepayment as price increases
  - Fuel poor become increasingly trapped in prepayment when price increases
  - Higher fuel consumption increases prepayment
    - Rather than prepayment helping manage it as “Energy UK” suggest
- Households that tend to be fuel poor suffer the bulk of this distortion
  - This is also exacerbated by household size, at certain house types, age, private and social rental tenures.
- Policy Implications:
  - Forcing higher fuel prices to the fuel poor creates a vicious circle for households that struggle to sufficiently heat their home
  - High fuel consumption increases prepayment, hence energy-efficiency/insulation may also contribute to taking people out of the fuel poverty trap
  - Smart meters and competitive price structuring available to all, should nullify this distortion and price-discrimination

Further Research

- Finalize current specification
  - Look at more spatial, building and behavioral characteristics
  - Extend the analysis to all domestic energy consumption
  - Enable welfare change estimation for range of policy initiatives to different household profiles
  - Attempt to incorporate external temperatures
- Estimate an unbiased energy demand model
  - There is obvious self-selection with regard to payment methods
  - Estimate a two step model that employs the logistic regression results

Thank you!

Sotirios Thanos
s.thanos@ucl.ac.uk