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**Preference for indoor ambient heating  
with explicit interpersonal influence**

J. Gibson & R. Scarpa

Contributed presentation at the 60th AARES Annual Conference,  
Canberra, ACT, 2-5 February 2016

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# AARES 2016 Canberra

## Preference for indoor ambient heating with explicit interpersonal influence

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February 2016



- NZ Government spent \$350m to subsidize retro-fitting of clean heating and insulation
- unclear what values the affected population place on improved heating
  - RCTs give the improved devices away for free
  - RCT projects asked participants how much they would pay, and reported values of one-fifth to one-half capital cost
- We use choice experiments to provide evidence on the willingness to pay (WTP) for clean heating and humidity control devices
  - Derived for a group that suffers from a high burden of respiratory disorders, has poor housing and mostly rent rather than own

## Pacific Island immigrants in Auckland and Hamilton

- Largest and 3rd largest cities in NZ in terms of Pacific populations
  - Damp, humid and temperate climate
    - $\approx$  inches per year rainfall, relative humidity of 85%
    - Mean annual temp  $15^{\circ}\text{C}$  (Auckland),  $14^{\circ}\text{C}$  (Hamilton)
    - July mean  $10.9^{\circ}\text{C}$  (Auckland),  $8.9^{\circ}\text{C}$  (Hamilton)
    - c.f. Pacific Islands mean  $23^{\circ}\text{C}$ , July mean of  $21^{\circ}\text{C}$
  - High proportion of housing stock constructed during leaky homes' period due to rapid population growth
  - Pacific Islands group reports lowest housing satisfaction
    - 33% find their house too cold vs 15% overall

# Sample Characteristics

- $N = 249$ , mostly Tongan plus assorted Melanesians
  - 43% males Survey included focus groups, split into male, female and youth (18-25), with age/ethnic specific survey team leaders
  - 47% high school quals, 22% no quals, 31% some tertiary (including trades)
  - 51% E/P rate (same as overall PI in HLFS, March 2013)
  - Mean income of \$21,500 (overall PI is \$24,900 which is one-third below national average)
- 82% renting (Tongans had 2<sup>nd</sup> lowest home ownership rate of any ethnic group in 2006 Census)
  - Even lower here because many are recent migrants
  - Average rent of \$311 per week (2013)
  - Hypothetical rent for owner-occupiers of \$377/week

# Housing Characteristics

- Important to capture these because choice experiment design pivots on current rental costs and dwelling characteristics
- → Capture several housing attributes

## Dwellings are crowded

- 8 residents per dwelling, 2.4 per proper bedroom
- garages and lounges often used for sleeping
- No difference between renters and owners
- High dissatisfaction with current housing
  - 73% have visible mould in one or more rooms
  - 61% find dwelling too cold
  - 78% find dwelling too difficult or costly to heat

# Choice experiment design

## Choices over various combinations of six improved heating/humidity control devices

% whose dwelling has this device

	Renters	Owners
Heat pump	7.8	4.5
Electric heater	56.1	38.6
Gas bottle heater (unflued)	6.3	0
In-built gas heater (flued)	24.4	22.7
Open fireplace	28.3	22.7
Enclosed wood burner	1.5	29.5
Dehumidifier	4.9	9.1
HRV (heat-recovery ventilation)	3.4	2.3

< 10% have improved devices that warm or dry the air (heat pumps, HRV, dehumidifiers)



Choices over various combinations of six improved heating/humidity control devices and variation in rent, for a dwelling like current one



## Methodological Steps

- general research area: content validity of stated preference methods for nonmarket valuation
- specific question: is the effect of influential advice detectable in preference structure?
  - 1) first choice experiment to elicit preferences
  - 2) group interaction and elicitation of interpersonal influence rating (self-reported)
  - 3) second choice experiment (identical)
  - 4) CE1 data analysis to derive utility structures of respondents (mixed logit)
  - 5) CE2 data analysis to investigate effects of influential subjects (mixed logit)
  - 6) joint estimation of CE1 and CE2 responses inclusive of effects (biv. probit panel rand. effects)

# Utility function

- Let  $j$  be the alternative,  $\beta_{kn}$  the utility weight for respondent  $n$  and related to attribute  $x_k$
- The utility function is assumed to be linear in the parameters, specifically

$$V_n = \beta_{1n}HRV + \beta_{2n}WDBRN + \beta_3ELHEAT + \beta_4GSHEAT + \beta_5HTPMP + \beta_{6n}DEHUM + \beta_7RNT + \beta_{8n}LFTALT \quad (1)$$

- The binary probability of heating system selection is logit:

$$\Pr(j) = [1 + \exp(\Delta V_n)]^{-1} \quad (2)$$

- Conditional on the estimates on the first set of choice experiments, using ex-post individual-specific coefficient estimates  $\hat{\beta}_n$ , the predicted differences for the utilities of the alternatives in the second experiments are derived for all respondents, denoted by  $\Delta \hat{v}_n$

# Utility function

- to test the effect of subjects who emerged as influential in the group discussion that preceded the second CE, the second estimation included for each subject the  $\Delta\hat{V}_n^*$  of the individual rated as most influential by the subject. The utility difference was:

$$\Delta V_n = \beta_{1n}HRV + \beta_{2n}WDBRN + \beta_{3n}ELHEAT + \beta_{4n}GSHEAT + \beta_{5n}HTPMP + \beta_{6n}DEHUM + \beta_{7n}RNT + \beta_{8n}LFTASC + \beta_9\Delta\hat{V}_n^* \quad (3)$$

- Several panel models were estimated, but three **preliminary** models are reported:
  - M1, all coefficients fixed, except  $\beta_9$  for  $\Delta\hat{V}_n^*$  ( $\ln \mathcal{L}^* = -1151.82$  up from  $\ln \mathcal{L}^* = -1211.1$  of the FC logit)
  - M2, coeff for *HRV*, *WDBRN*, *DEHUM*, *LFTASC* random ( $\ln \mathcal{L}^* = -1150.78$ , improving by )
  - M3, coeff for *HRV*, *WDBRN*, *DEHUM*, *LFTASC* &  $\Delta\hat{V}_n^*$  random ( $\ln \mathcal{L}^* = -1143.32$ )

# Model from choice experiment 1, used to derive $\Delta \hat{V}_n^*$

```

Integration points = 7                               Wald chi2(7)    =    328.41
Log likelihood = -1207.9902                         Prob > chi2    =    0.0000
    
```

y1	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
HRV	1.188651	.1001005	11.87	0.000	.9924575	1.384844
WDBRN	.2878129	.078457	3.67	0.000	.1340401	.4415857
EL_HEAT	.165717	.0829755	2.00	0.046	.0030881	.3283459
GS_HEAT	-.1254903	.0705511	-1.78	0.075	-.263768	.0127874
HT_FMP	.4059491	.0831338	4.88	0.000	.2430099	.5688884
DEHUM	.2107795	.0769324	2.74	0.006	.0599949	.3615642
RNT	-.1381863	.0082072	-16.84	0.000	-.154272	-.1221006
_cons	.213063	.055941	3.81	0.000	.1034206	.3227054

Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]	
ric_id: Independent				
sd(HRV)	.5736472	.1522585	.3409709	.9651001
sd(WDBRN)	.257951	.3598055	.0167583	3.97049
sd(DEHUM)	.1615956	.4316731	.0008602	30.35703
sd(_cons)	.2526475	.1683849	.0684235	.9328783

```

LR test vs. logistic model: chi2(4) = 6.20          Prob > chi2 = 0.1847
    
```

# M3 from choice experiment 2, used to test the effect of $\Delta \hat{V}_n^*$ on respondents (does the opinion of influential subjects in the group matter?)

Log likelihood = -1143.3178                      Prob > chi2                      =                      0.0000

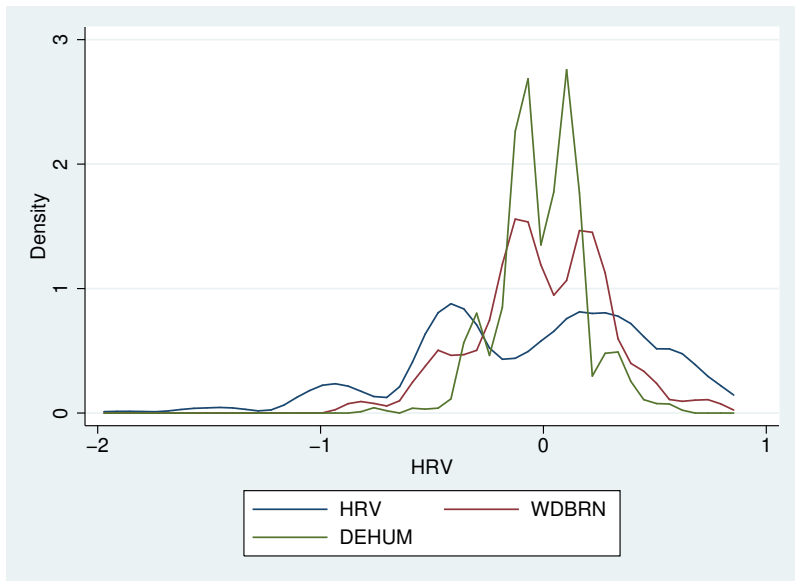
y2	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
HRV	1.836619	.1517473	12.10	0.000	1.539199	2.134038
WDBRN	.5479028	.1064417	5.15	0.000	.339281	.7565246
EL_HEAT	.275418	.0979282	2.81	0.005	.0834823	.4673538
GS_HEAT	-.1616177	.0829161	-1.95	0.051	-.3241302	.0008948
HT_PMP	.4948139	.1034528	4.78	0.000	.2920501	.6975778
DEHUM	.2501789	.096971	2.58	0.010	.0601192	.4402386
RNT	-.1515577	.0101657	-14.91	0.000	-.1714821	-.1316332
dv_max	-.0850759	.063111	-1.35	0.178	-.2087711	.0386193
_cons	.3223119	.0738496	4.36	0.000	.1775694	.4670544

Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]	
ric_id: Independent				
sd(HRV)	.9543458	.1773332	.6630381	1.37364
sd(WDBRN)	.6995695	.2155482	.3824392	1.279674
sd(DEHUM)	.5300303	.2060729	.2473763	1.135647
sd(dv_max)	.5477547	.0976695	.3861975	.776896
sd(_cons)	.507882	.125234	.3132368	.8234796

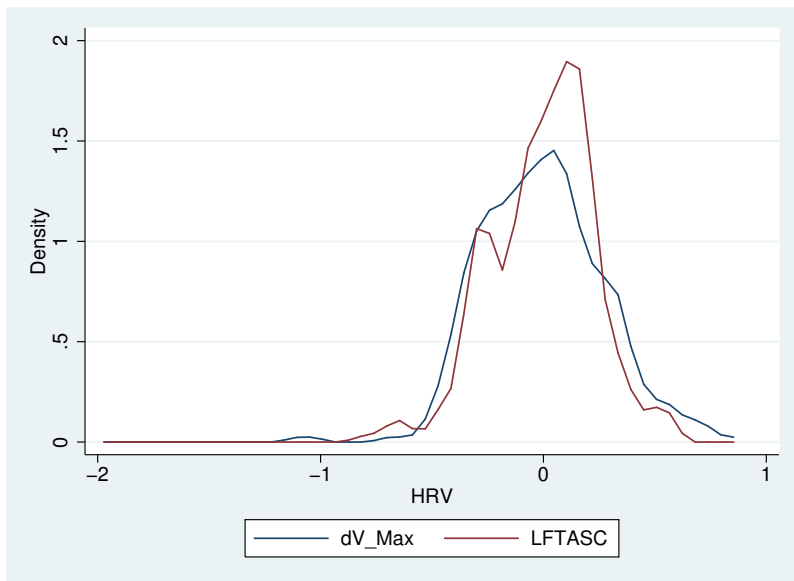
LR test vs. logistic model: chi2(5) = 38.28

Prob > chi2 = 0.0000

# Individual-specific $\hat{\beta}_n$ for heating attributes from M3



# Individual-specific $\hat{\beta}_n$ for $\Delta \hat{V}_n^*$ and *LFTASC* from M3





# Panel random effect bivariate probit, structural parameters of $y_1$ and $y_2$

Mixed-process multilevel regression      Number of obs      =      2,241  
 Wald chi2(15)      =      474.58  
 Log pseudolikelihood = -2178.0665      Prob > chi2      =      0.0000

		Robust				[95% Conf. Interval]	
	Coef.	Std. Err.	z	P> z			
<hr/>							
$y_1$							
	HRV	.6541297	.0472722	13.84	0.000	.5614779	.7467815
	WDBRN	.1497143	.045076	3.32	0.001	.0613669	.2380618
	EL_HEAT	.0694203	.0482305	1.44	0.150	-.0251097	.1639503
	GS_HEAT	-.0749377	.0426179	-1.76	0.079	-.1584673	.0085919
	HT_PMP	.2222403	.0466972	4.76	0.000	.1307155	.3137651
	DEHUM	.1237378	.0444535	2.78	0.005	.0366105	.2108651
	RNT	-.0781916	.0047331	-16.52	0.000	-.0874683	-.0689149
	_cons	.1153765	.031666	3.64	0.000	.0533123	.1774406
<hr/>							
$y_2$							
	HRV	.83365	.0606295	13.75	0.000	.7148184	.9524816
	WDBRN	.2403346	.0545092	4.41	0.000	.1334985	.3471707
	EL_HEAT	.0892143	.0586154	1.52	0.128	-.0256697	.2040983
	GS_HEAT	-.079254	.0496309	-1.60	0.110	-.1765288	.0180207
	HT_PMP	.2129174	.0555464	3.83	0.000	.1040485	.3217864
	DEHUM	.1204776	.0536291	2.25	0.025	.0153665	.2255887
	RNT	-.0750152	.0054087	-13.87	0.000	-.0856162	-.0644143
	<span style="border: 1px solid red; padding: 2px;">dv_max</span>	<span style="border: 1px solid red; padding: 2px;">-.046791</span>	<span style="border: 1px solid red; padding: 2px;">.0292741</span>	<span style="border: 1px solid red; padding: 2px;">-1.60</span>	<span style="border: 1px solid red; padding: 2px;">0.110</span>	<span style="border: 1px solid red; padding: 2px;">-.1041672</span>	<span style="border: 1px solid red; padding: 2px;">.0105852</span>
	_cons	.1261202	.0371882	3.39	0.001	.0532327	.1990078
<hr/>							
	/lnsig_1_1	-2.057918	.5764079	-3.57	0.000	-3.187657	-.9281796
	/lnsig_1_2	-1.460889	.2237485	-6.53	0.000	-1.899428	-1.02235
	/atanhrho_~12	.3979982	.5885502	0.68	0.499	-.7555389	1.551535
	/atanhrho_12	.8684406	.0514067	16.89	0.000	.7676853	.969196

# Panel random effect bivariate probit, cross equation covariance for $y_1$ and $y_2$

Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]	
Level: ric_id				
y1				
Standard deviations				
_cons	.1277196	.0736186	.0412684	.3952726
y2				
Standard deviations				
_cons	.23203	.0519164	.1496543	.3597487
Cross-eq correlation				
y1                y2				
_cons                _cons	.3782348	.5043512	-.6384418	.9140384
Level: Residuals				
Standard deviations				
y1	1	(constrained)		
y2	1	(constrained)		
Cross-eq correlation				
y1                y2	.700581	.0261756	.6455815	.7483508

## Conclusions

- Influence of subjects has a variable effect, but it is detectable
- Utility measures (marginally) improve both separate and simultaneous preference estimation in panel data
- Preference for heating devices are mostly stable across experiments

## Way forward

- Refine the influence effects separately at the attribute level (rather than at the overall utility level)
- Move to a simultaneous estimation (Structural Choice Models?) to achieve efficiency