<u>Research Outline</u>

Policy choice in a complicated health insurance market: Do people get it right?

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Abstract: This paper evaluates health insurance policy selection by conducting a discrete choice experiment using policies closely calibrated to the Australian private health insurance market. The experimental approach used in this paper affords considerable control over the choice environment and overcomes some limitations of revealed preference research. Preliminary results suggest that people frequently make choices that are inconsistent with rational utility maximisation and that choice quality is particularly low when choosing combined hospital and ancillaries insurance. Future work will explore the cause and consequence of this behaviour and in particular test for the role of heuristic decision making strategies.

1 Introduction

A growing body of evidence suggests that consumer choices in health insurance cannot be adequately captured by the traditional rational behaviour model. Decisions appear to be heavily influenced by choice complexity, information and comparison frictions (Kling et al., 2012; Handel & Kolstad, 2015), inertia (Handel, 2013; Handel & Kolstad, 2015; Polyakova, 2015), heuristics (Bhargava et al., 2015) and various behavioural biases. Surveys asking people to answer questions about health insurance contracts demonstrate limited comprehension (Hibbard et al., 1998; Lowenstein et al., 2013). Experimental research suggests that comprehension is even lower when consumers are presented with larger choice sets (Hanoch et al., 2009; Barnes et al., 2014).

In this paper I conduct a discrete choice experiment (DCE) to study behaviour in a complicated health insurance environment, specifically the

Australian private health insurance market. This market is characterised by many of the features that appear to limit consumers' ability to make optimal policy choices. The number of policies available is large ranging from 48 to 2050 across each state for policies that include ancillaries coverage. While price is heavily regulated in Australia, insurers have more flexibility over policy design and consequently the benefit structure for policies is typically complicated. For example, policies differ with regard to what services they cover, co payment rates and structures, deductibles, network service providers, loyalty bonuses, waiting periods for initial claims and annual limits on benefits.

There is concern among stakeholders that the complexity of health insurance has a detrimental effect on consumer choices (PHIAC, 2013; ACCC, 2015; Deloitte Access Economics, 2012). However, the limited availability of data on actual policy choices means that evidence of this is scarce. By using a DCE to elicit preferences, this study overcomes this data constraint. A novel aspect of this study is that it considers the extent to which product bundling, specifically the bundling of hospital and ancillaries health insurance, affects choice quality. Most health insurance contracts include combined coverage for these services (around 85%). While bundling could satisfy the preferences of consumers it increases complexity of the health insurance policy, which may negatively affect choice quality.

2 Sample

Respondents were recruited through the survey company Qualtrics' online panels. 1,528 people completed the DCE and were evenly assigned to two treatments[1] (discussed in the next section). People aged 25-64 years were invited to complete the survey and quotas for age, sex and education level were used to improve representativeness[2]. Responses were collected between 10-21 December 2015 (just under 70% of these responses were collected between 15-16 December). The average response time was 16 minutes. Of those who started the survey, 44% completed. 263 people were ejected from

[1] The final sample is not perfectly balanced because 6 respondents in treatment 2 were inadvertently shown an incorrect choice set. These observations are dropped in the regression analysis.

[2] The 2011 Census was used to create quotas for: people aged 25-34 years; 35-44 years; 45-54 years; 55-64 years; sex; and people with university degrees or higher.

the survey because they failed an attention filter[3]. In addition to the DCE questions, the survey collected information on respondents' basic demographics (e.g. age, sex, education, relationship status, employment), self-assessed health, health care utilisation and expected utilisation, risk aversion, health insurance status, health insurance literacy and household income.

Table 1 provides summary statistics for some of the main variables used in the analysis and compares them to population benchmarks. Overall, the sample is fairly representative of the population and balanced across treatments. Where there are discrepancies, these are generally not economically large. Note the sample slightly over-represents people in the 55-64 years age group due to a coding error that resulted in extra respondents in this group completing the survey (importantly this does not affect the balance between treatments).

3 Experimental design

The DCE required respondents to identify a preferred private health insurance policy from a choice of two competing policies a total of 8 times. Examples of the choice task are provided in Figures 1 and 2. The policies were designed to cover a single adult for a period of 12 months and respondents were instructed to choose as if they were purchasing insurance for themselves only. The experiment included two treatment groups; a group whose choice task involved ancillaries only health insurance policies (T1) and a group whose choice task involved combined ancillaries and hospital health insurance policies (T2). To generate the choice sets, a two block D-efficient fractional factorial design was implemented to using SAS (Kuhfeld, 2010)[4].

To analyse choice quality, the experimental design focuses in particular on eliciting preferences for ancillaries health services. This exploits a convenient detail in the structure of insurance for ancillaries health services. Specifically, the benefits for these services are subject to annual limits (caps). Preferences

[3] The attention filter was a 5-point scale question matrix asking respondents how satisfied they were with their life, neighbourhood, financial situation and then the filter question that instructed them to choose 'dissatisfied'.

[4] The covariance matrix of a multinomial logit model with zeros for all coefficients was used. The choice set in T2 was updated based on pilot estimates. This was because the initial choice set included two highly undesirable options, one of which was never chosen. There was no such issue with T1.

that imply willingness to pay for these features in excess of these caps violate rational utility maximisation. This approach to assessing choice quality has the advantage over most revealed preference work of not requiring any assumptions about the degree of risk aversion or expected health care costs.

The attribute levels and included policy features (see Table 2) were chosen based on an extensive search of policies listed on the Private Health Insurance Ombudsman's (PHIO's) information website www.privatehealth.gov.au. The PHIO website stores details on every policy available in Australia with the information presented in heavily regulated Standard Information Statements (SIS). The SIS are intended to facilitate simple comparison of policies for consumers. Search was restricted to basic and medium level policies since higher level policies are unlikely to be attractive to many people (in particular the uninsured) and necessarily include more attributes than is feasible to include in a DCE. The information provided to respondents in the DCE was similar in structure and content to the SIS. The study therefore provides a useful insight into the effectiveness of this government regulated choice architecture.

4 Empirical model

The standard motivating model for estimating preferences in the DCE literature is the random utility model (McFadden, 1973). Individual i is assumed to receive utility from policy choice j in scenario s according to the following function.

$$U_{ijs} = x^{'}_{ijs}\boldsymbol{\beta}_i + \epsilon_{ijs} \quad i = 1, \ldots, N; j = 1, \ldots, J; s = 1, \ldots, S \tag{1}$$

Utility depends on a vector of policy attributes $x^{'}_{ijs}$ with preference weights $\boldsymbol{\beta}_i$ that may vary across individuals and ϵ_{ijs} is a random error term.

To allow for preference heterogeneity (random coefficients), this paper will estimate mixed logit (MXL) and generalised multinomial logit (G-MNL) (Fiebig et al., 2010) models. The G-MNL nests the MXL specification when preferences follow a multivariate normal distribution and incorporates both heterogeneity in preferences and heterogeneity in the variance of the error term (scale heterogeneity) while also allowing for dependence in choices made by the same individuals across scenarios. G-MNL assumes the following functional form for coefficient estimates:

$$\boldsymbol{\beta}_i = \sigma_i \boldsymbol{\beta} + \{\gamma + \sigma_i(1-\gamma)\}\eta_i \tag{2}$$

where η_i is a random term that captures preference heterogeneity. It is assumed multivariate normal i.e. $\eta_i \sim MVN(0, \Sigma)$. γ is a scalar that influences the degree to which scale heterogeneity shifts the standard deviation of the coefficient estimates. To ensure positive values, σ_i is assumed to follow a log-normal distribution with $\sigma_i = \exp(\bar{\sigma} + \tau \upsilon_i)$, where $\bar{\sigma}$ is a normalising constant and $\upsilon_i \sim N(0, 1)$.

5 Preliminary results and expectations

5.1 Dominated choices

The hypothetical choice sets included some options that were financially dominated. While there were no purely dominated options (i.e. options where every feature was worse for one policy compared to the alternative policy), financially dominated policies occurred where Policy A(B) was worse or no better than Policy B(A) on every feature but one and the maximum financial gain from that feature was less than the annual increase in the premium. Each block involved one scenario with a dominated policy so that every respondent faced a dominated policy once. For example, in T1 block 1, choosing Policy A involved a \$140 increase in the annual premium for a maximum possible gain of \$100 in the cap for massage. There was a similar trade-off in T1 block 2 involving increased coverage of natural therapies. In T2 the policies involving dominated options included a higher insurer's co payment rate that was insufficient to offset the premium increase.

Measuring the proportion of people who choose a financially dominated policy when presented to them is one non-parametric test for choice quality. The challenge is interpretation, specifically whether such choices are the result of choice strategies that depart from rational utility maximisation or are simply random error or non-compliance. My results suggest that these choices are at least in part attributable to a heuristic decision making strategy of narrow focus. Specifically, in T1 block 1 (block 2) respondents who utilised massage (natural therapies) in the previous 12 months are significantly more likely to choose the dominated policy. These results are presented in Table 3, where linear probability models are estimated with a dummy equal to 1 if the respondents chose a dominated policy as the dependent variable. The only other variable that consistently predicts choosing a dominated policy is a measure of health insurance comprehension, which has the expected negative sign.

5.2 Preferences

Preferences have been estimated using the MNL and G-MNL models. However, further refinement is needed, particularly with regard to the latter specification and it is pertinent to highlight that results are preliminary and incomplete.

The main focus is on the estimation for common attributes (i.e. ancillaries health services) across T1 and T2. These preferences are compared across treatments and against rational benchmarks. Assuming that the utility function is linear and hospital services are independent of ancillaries services (or at least not compliments), willingness to pay (WTP) for identical product features should not be higher in T2 than T1.

The results are in Tables 4 and 5. The first striking result is that WTP estimates (measured as the annualised ratio of the attribute and price coefficient) are generally much higher in T2 than T1, counter to utility maximisation expectations. For example, focusing on the G-MNL results, median WTP for increasing coverage of general dental from $350 to $700 is $64 in T1 and $268 in T2. There are also large differences for optical, physical health services and natural therapies. The second striking result is that in T2 a significant number of people display irrational preferences in the sense that WTP exceeds the maximum increase in annual benefits. For example, the median WTP is $151 to increase the annual cap on optical from $150 to $300, which is a clear violation of rationality. Consistent with other recent evidence that consumers place too much weight on reductions in excesses (Shapira & Venezia, 2008; Sydnor, 2010), the median WTP for a reduction in the excess of $500 to $250 is $585, which is more than double what any rational consumer should be willing to pay.

5.3 Individual coefficients

To explore further the magnitude of choice inconsistency, individual coefficients will be simulated following the method of Revelt and Train (2000). This will allow the calculation of WTP for each individual in the sample and facilitate identification of those individuals with irrational WTP. Cluster analysis will be performed to test what factors can explain such preferences. For example, the results on dominated policies suggest a narrow focus heuristic, whereby people with high expected utilisation for a particular health service simplify the choice task by narrowing their focus to coverage for that service. Health insurance comprehension, education and familiarity with the product (i.e. insurance status) may also be important.

5.4 Policy simulation

Although the results suggest people frequently depart from rational utility maximisation, this does not mean that real world choices will be low quality. Depending on the structure of the market, alternative simplifying choice strategies may do a reasonable job of approximating rational utility maximisation. To gain some insight on this, the study will use the estimated individual preferences to simulate policy choices within a realistic menu of policies that could represent offerings by a single insurer. Data that was collected on utilisation and expected utilisation will be used to predict expected health service expenditure and assess simulated choice quality.

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Table 1: Descriptive statistics (mean values)

Variable	T1	T2	All	Population
Age 25-34	0.240	0.216	0.228	0.258
Age 35-44	0.217	0.251	0.234	0.267
Age 45-54	0.226	0.228	0.227	0.257
Age 55-64	0.317	0.305	0.311	0.218
Sex	0.454	0.530	0.492	0.493
University	0.284	0.246	0.265	0.265
Couple	0.594	0.644	0.619	0.635
Employed	0.628	0.605	0.616	0.713
HH income				
<$60K	0.445	0.427	0.435	0.430
$60K–<$125K	0.386	0.397	0.392	0.336
$125K+	0.169	0.176	0.173	0.235
PHI(hospital)	0.490	0.493	0.491	0.51
PHI (ancillaries)	0.505	0.497	0.501	0.54

Note: Sample size is 1,528 (764 in each treatment). Have used PHIAC/APRA numbers (December 2011) and the 2011 ABS Census for PHI coverage. Since coverage has grown overtime, these figures are probably higher today. Population estimates for the income distribution come from the 2012 wave of the Household Income and Labour Dynamics in Australia Survey.

Table 2: Attributes and levels

Attribute	T1 Levels	T2 Levels	Average annual benefits (share)
Premium	$14.17, $20, $25.83, $31.67	$100, $112.5, $125, $137.5	
Ancillaries features			
Insurer's co-payment rate	60%, 70%	60%, 70%	
General dental	$350, $700	$350, $700	
Optical	$150, $300	$150, $300	
Physical health services	$0, $150, $300	$0, $150, $300	
Natural therapies	$0, $100	$0, $100	
Remedial massage	$0, $100	$0, $100	
Hospital features			
Inclusions		Low, Medium, High	
Excess		$500, $250	
Services coverage		8/10 services receive benefits, 9/10 services receive benefits	

Note: For ancillaries health services the figures are the annual caps on claims. Physical health services are a combined cap for physiotherapy, chiropractic, osteopathy and acupuncture. Low inclusions are palliative care, psychiatric and rehabilitation. Medium inclusions are low inclusions plus cataract and eye lens procedures, gastric banding and related services and sterilisation. High inclusions are medium inclusions plus cardiac and cardiac related services and hospital treatment for which Medicare pays no benefit (e.g. cosmetic surgery).

Figure 1: Example of treatment 1 choice task

Feature	Policy A	Policy B
Monthly premium	$31.67	$20.00
Insurer's co-payment rate	60%	70%
General dental	$350	$700
Optical	$150	$300
Physiotherapy; chiropractic; osteopathy; acupuncture	$300	$0
Naturopathy	$0	$100
Remedial massage	$0	$100

○ Policy A

○ Policy B

Note: For ancillaries health services the figures are the annual caps on claims. For example, $350 for general dental means that the maximum benefits the policy will pay for general dental services is $350 each year. Respondents could hover the mouse over each feature to get a detailed description of what health services they could expect to be covered for.

Figure 2: Example of treatment 2 choice task

	Policy A	Policy B
Monthly premium	$137.50	$100.00
Hospital features		
What is covered if I have to go to hospital?	· Doctor's bills in hospital · Ambulance fees	· Doctor's bills in hospital · Ambulance fees
What services are not covered at all (exclusions)?	x Pregnancy and birth related services x Assisted reproductive services x Joint replacements ie shoulder, knee, hip and elbow, including revisions x Dialysis for chronic renal failure x Cataract and eye lens procedures x Gastric banding and related services x Sterilisation x Cardiac and cardiac related services x Hospital treatment for which Medicare pays no benefit eg most cosmetic surgery	x Pregnancy and birth related services x Assisted reproductive services x Joint replacements ie shoulder, knee, hip and elbow, including revisions x Dialysis for chronic renal failure
What services are only covered to a limited extent (restrictions, benefit limitations periods)?	✓ Palliative care ✓ Psychiatric services ✓ Rehabilitation	✓ Palliative care ✓ Psychiatric services ✓ Rehabilitation ✓ Cataract and eye lens procedures ✓ Gastric banding and related services ✓ Sterilisation ✓ Cardiac and cardiac related services ✓ Hospital treatment for which Medicare pays no benefit eg most cosmetic surgery
Doctors and hospital bills	9/10 medical services paid by this health insurance policy have no out-of-pocket expenses	8/10 medical services paid by this health insurance policy have no out-of-pocket expenses
Excess	$500	$500
Co-payment	None	None
Ancillaries features		
Insurer's co-payment rate	70%	60%
General dental	$700	$350
Optical	$300	$300
Physiotherapy; chiropractic; osteopathy; acupuncture	$300	$0
Naturopathy	$100	$0
Remedial massage	$0	$0

Table 3: People choosing financially dominated options

Variable	All	T1	T2	T1, B1	T1, B2
sex	0.033	-0.006	0.059*	0.012	0.004
	(0.021)	(0.027)	(0.032)	(0.040)	(0.037)
age	-0.001	-0.003**	0.001	-0.002	-0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
city	0.020	0.018	0.019	-0.077*	0.097**
	(0.022)	(0.029)	(0.034)	(0.042)	(0.039)
sa_riskav	-0.006	0.012	-0.018	-0.004	0.040
	(0.014)	(0.018)	(0.022)	(0.027)	(0.024)
university	-0.012	-0.060*	0.046	-0.006	-0.097**
	(0.025)	(0.032)	(0.039)	(0.048)	(0.042)
couple	-0.006	-0.004	-0.008	-0.031	0.020
	(0.021)	(0.027)	(0.033)	(0.040)	(0.037)
excell	0.090	0.079	0.084	0.086	0.055
	(0.055)	(0.072)	(0.083)	(0.115)	(0.090)
vgood	0.012	-0.031	0.045	-0.082	0.006
	(0.045)	(0.058)	(0.070)	(0.092)	(0.073)
good	0.035	-0.029	0.086	-0.063	0.005
	(0.045)	(0.057)	(0.069)	(0.093)	(0.071)
fair	0.021	-0.009	0.048	-0.049	-0.012
	(0.047)	(0.060)	(0.074)	(0.095)	(0.076)
no_phi	-0.018	-0.001	-0.037	0.007	0.010
	(0.022)	(0.028)	(0.033)	(0.041)	(0.038)
phi_litALL	-0.141***	-0.146***	-0.139***	-0.185***	-0.093**
	(0.027)	(0.036)	(0.041)	(0.055)	(0.047)
Massage visit				0.102**	
				(0.051)	
Naturo visit					0.272***
					(0.083)
_cons	0.243***	0.310***	0.196	0.413**	0.067
	(0.082)	(0.101)	(0.132)	(0.161)	(0.131)
N	1522	764	758	382	382

*,**,*** significant at 10%, 5%, 1% respectively.

Table 4: Regression results - Treatment 1

	MNL		GMNL		
Variable	Coeff. (SE)	WTP [95% CI]	Coeff. (SE)	SD (SE)	WTP [25%-75%]
Ancillaries features					
Premium	-0.069	1.00	-0.465	0.310	
	(0.004)	.	(0.195)	(0.115)	.
Co-payment	-0.074	-12.81	0.126	0.115	2.54
	(0.029)	[-22.70,-2.92]	(0.148)	(0.218)	[-44.18,49.94]
Dental	0.486	84.31	3.179	2.342	64.48
	(0.038)	[70.10,98.51]	(1.331)	(0.880)	[15.78,130.93]
Optical	0.201	34.96	1.316	1.411	26.17
	(0.031)	[24.45,45.47]	(0.566)	(0.517)	[-19.56,78.80]
Physical 2	0.390	67.71	2.186	0.109	43.84
	(0.040)	[53.26,82.16]	(0.908)	(0.177)	[-2.42,102.33]
Physical 3	0.407	70.59	2.969	1.555	60.11
	(0.046)	[55.30,85.88]	(1.272)	(0.639)	[12.04,125.07]
Naturopathy	0.152	26.32	0.772	1.411	15.18
	(0.031)	[16.13,36.52]	(0.358)	(0.574)	[-30.42,64.73]
Massage	0.059	10.19	0.457	1.521	9.20
	(0.037)	[-2.49,22.86]	(0.255)	(0.658)	[-36.99,57.65]
$\hat{\tau}$			1.969		
			(0.311)		
$\hat{\gamma}$			0.116		
			(0.055)		
LL	-3636.24		-3387.89		
BIC	7347.77		6945.19		

Note: Note: N=12,224. Individual clustered standard errors. MNL WTP standard errors calculated using delta method. GMNL estimated using Stata gmnl command (Gu et al., 2013) with 500 draws in simulation. WTP estimates in the GMNL model based on 1000000 psuedorandom draws. *,**,*** significant at 10%, 5%, 1% respectively.

Table 5: Regression results - Treatment 2

	MNL		GMNL		
Variable	Coeff. (SE)	WTP [95% CI]	Coeff. (SE)	SD (SE)	WTP [25%-75%]
Ancillaries features					
Premium	-0.011	1.00	-0.038	0.037	
	(0.001)	.	(0.015)	(0.004)	.
Co-payment	0.064	71.55	0.016	0.091	4.82
	(0.032)	[1.70,141.40]	(0.181)	(0.141)	[-61,65,67.39]
Dental	0.304	339.88	0.965	0.643	267.68
	(0.037)	[224.61,455.15]	(0.308)	(0.092)	[25.92,328.91]
Optical	0.173	193.88	0.527	0.054	150.98
	(0.042)	[81.79,305.97]	(0.249)	(0.275)	[-2.15,196.13]
Physical 2	0.029	32.72	0.473	0.514	136.15
	(0.044)	[-63.43,128.88]	(0.226)	(0.111)	[-6.39,180.75]
Physical 3	0.204	228.16	1.062	0.570	293.02
	(0.040)	[116.36,339.97]	(0.403)	(0.104)	[29.01,359.29]
Naturopathy	0.035	39.70	0.865	0.559	241.95
	(0.040)	[-49.28,128.67]	(0.409)	(0.110)	[20.33,298.10]
Massage	0.045	50.66	0.235	0.574	69.14
	(0.038)	[-32.78,134.10]	(0.183)	(0.091)	[-30.14,116.10]
Hospital features					
Inclusions 2	0.212	236.74	1.376	0.220	374.14
	(0.042)	[119.03,354.46]	(0.447)	(0.162)	[43.71,458.05]
Inclusions 3	0.669	748.53	2.819	0.524	737.82
	(0.051)	[514.22,982.84]	(0.746)	(0.123)	[85.08,919.85]
Excess	0.384	429.36	2.211	0.480	585.46
	(0.036)	[301.90,556.82]	(0.784)	(0.137)	[68.49,724.56]
Services	0.156	174.67	0.439	0.128	126.81
	(0.033)	[90.51,258.83]	(0.274)	(0.166)	[-8.98,171.06]
$\hat{\tau}$			2.274		
			(0.286)		
$\hat{\gamma}$			1.171		
			(0.098)		
LL	-3909.15		-3755.26		
BIC	7931.15		7755.00		

Note: Note: N=12,128. Individual clustered standard errors. MNL WTP standard errors calculated using delta method. GMNL estimated using Stata gmnl command (Gu et al., 2013) with 500 draws in simulation. WTP estimates in the GMNL model based on 1000000 psuedorandom draws. *,**,*** significant at 10%, 5%, 1% respectively.