### Discrete Choice Modelling: How good is the model?

### Model Selection and Goodness of fit NZ Freight Shipper's Mode Choice and Modal Shift Behaviour

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## **Discrete Choice Modelling**

- Transport consumer behavior exhibits substantial heterogeneity (Variations in travel behaviors)
  - 1. Want to understand causes of those variations
  - 2. Want to identify how to change travel behaviors (need elasticity values)
- Discrete choice modelling enables us to capture travel behavior and mode choice in particular
- When introducing a new transport service (e.g. Public transport, Cycle path, BRT, Light rail and etc.), it is particularly important;
  - Service positioning and advertisement
  - Level of service (e.g. service frequency)
  - Optimal price (e.g. WTP and WTA)

### New Trends in Discrete Choice Modelling

Increasing Complexity \*

- In the early stages, Multinomial Logit (MNL) model: the simplest and most popular
  - In the logit model, the utility of person *i* for alternative *j* is

 $U_{ij} = \beta X_{ij} + \varepsilon_{ij}$ 

 Over the last 10 years, Mixed Logit (MXL) model replaced ML model

 $U_{ij} = \beta_i X_{ij} + \varepsilon_{ij}$ 

 Now, Generalized Mixed Logit (GMXL) Model

(Fiebig et al. 2009)

 $U_{ijt} = [\sigma_i\beta + \gamma\eta_i + (1-\gamma)\sigma_i\eta_i]X_{ijt} + \varepsilon_{ijt}$ 

## NZ Freight Shipper Survey

### Stated Preference (SP) Survey (2012)

- <u>233</u> NZ freight Shippers
- <u>4,194</u> Choice experiments

### Four business divisions

- primary sector
- manufacturers
- retailers/wholesalers and
- freight logistics providers
- Ten industry sectors
- Analysed by MNL, ML, GMXL and Latent Class (LC) model

### **Respondent Grouping Systems**



## Goodness-of-Fit (Overall)

#### Preferred Measures:

- Lower Log-likelihood, AIC and BIC (Akaike and Bayesian Information Criterion)
- Higher Pseudo R<sup>2</sup>



# Summary of Model Results (Choice Set 1\*)

	MNL§		ML		GMXL		
Attributes	Coeff.	S. E.	Coeff.	S. E.	Coeff.	S. E.	
Random parameters: Mean							
TIME	-0.022***	0.007	-0.006	0.017	-0.098	0.089	
FREQ	0.197*	0.118	0.489**	0.214	1.377	0.869	Main Effects
Non-random parameters							(Mean)
COST	-0.002***	0.001	-0.004***	0.001	-0.004***	0.001	(MEall)
RELIAB	0.018	0.015	0.090***	0.026	0.085	0.140	
ASCS (Sea)	0.878	0.173	2.571	2.634	1.187	7.233	J_ASCs
ASCR (Rail)	-0.227	0.873	0.989	2.159	-0.902	7.800	
			1				
TIME*NTRUCK	0.006*	0.003	0.033**	0.015	0.072**	0.036	
SLIFE (Sea)	-0.797***	0.293	0.450	.320	1.403	3.945	Interaction
LTSP (Sea)	0.775***	0.254	1.744*	0.990	-1.439	3.308	Effects
NTSP(Rail)	-0.685*	0.407	-1.101	1.905	2.256	8.466	
EVOL (Rail)	-0.677*	0.408	-0.432	1.114	9.056	15.91	
LTSP (Rail)	0.742***	0.276	1.111	0.801	-1.437	2.308	_
			Random par	ameters: St	andard Deviation		Main Effects
TIME	-	-	0.129***	0.017	0.068	0.054	
FREQ	-	-	0.967***	0.127	1.552	1.145	(SD)
Variance parameter in scale (7)					0.878**	0.389	
Weighting parameter ( $\gamma$ )					0.000	0.478	
Sample mean ( $\sigma$ )					0.695	0.885	
Model Statistics							
Log Likelihood		-557.36		-273.15		263.41	
Pseudo R <sup>2</sup>		1144 7		580 3		0.596	Model
		1210 5		654.9		648.2	Statistics
Observations		828		828		876	

§MNL: All non-random parameters, \*\*\* p<0.01, \*\* p<0.05, \*p<0.1

## **Policy Implication**

- Estimated Current Mode Shares for Inter-Island Domestic Freight Movement
- Three–Mode Competition (Road vs Rail vs Sea)

	Road	Rail	Sea
Richard Paling Consulting (2008): Inter-island	12.4%	56.8%	30.8%
Rockpoint (2009) : Auckland - Christchurch	19.0%	38.0%	43.0%
This Study (2014) : based on Mixed Logit estimation	16.5%	59.1%	24.4%

#### Scenarios

- Increase Road Transport Cost
- Decrease Sea & Rail Cost
- Decrease Sea & Rail Transport Time
- Increase Sea & Rail Reliability

### Policy Implications and Modal Shift Estimations for Road, Sea, and Rail



# Conclusions

- In choice modelling, there is growing interest in incorporating preference heterogeneity and scale heterogeneity
- GMXL model may provide better model fit than ML model and can better explain
  - the behavior of extreme transport users who exhibit near lexicographic preference (i.e. people who care greatly about particular attributes)
  - the behavior of highly random customers whose choices are relatively insensitive to service attributes (i.e. people who have small attribute weights or a large scale of the error term)



# New research topic?

### Modal shift research to sustainable transport modes Urban freight transport demand model