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Modelling heterogeneity in scale directly: implications for estimates of influence in freight decision-making groups

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Abstract

The state of practice in the modelling of heterogeneous preferences does not separate the effects of scale from estimated mean and standard deviation preference measures. This restriction could lead to divergent behavioural implications relative to a flexible modelling structure that accounts for scale effects independently of estimated distributions of preference measures. The generalised multinomial logit (GMNL) model is such an econometric tool, enabling the analyst to identify the role that scale plays in impacting estimated sample mean and standard deviation preference measures, including confirming whether the appropriate model form approaches standard cases such as mixed logit. The GMNL model is applied in this paper to compare the behavioural implications of the minimum information group inference (MIGI) model within a study of interdependent road freight stakeholders in Sydney, Australia. MIGI estimates within GMNL models are compared with extant mixed logit measures (see Hensher and Puckett, 2008) to confirm whether the implications of the restrictive (with respect to scale) mixed logit model are consistent to those from the more flexible GMNL model. The results confirm the overall implication that transporters appear to hold relative power over supply chain responses to variable road-user charges. However, the GMNL model identifies a broader range of potential group decision-making outcomes and a restricted set of attributes over which heterogeneity in group influence is found than the mixed logit model. Hence, this analysis offers evidence that failing to account for scale heterogeneity may result in inaccurate representations of the bargaining set, and the nature of preference heterogeneity, in general.

Keywords: *Scale effects, group decision-making, road pricing, urban freight, generalised multinomial logit*

1. Introduction

A 2004 choice study of interdependent road freight stakeholders in Sydney yielded important estimates of preference and relative influence in freight decision-making groups (see Hensher and Puckett, 2007, 2008). These estimates were obtained through the use of a series of generalised mixed logit models that incorporated distributional assumptions on the heterogeneous preferences of respondents. Whilst the modelling techniques in the study were advanced relative to the state of practice in general, Fiebig et al. (2010) raise an important question of direct relevance to the policy implications of the study. That is, how would the conclusions reached in the study change if preference heterogeneity were estimated within a framework that explicitly accounts for scale heterogeneity?

The generalised multinomial logit (GMNL) model (see Keane, 2006) allows for the simultaneous estimation of preference heterogeneity (i.e., random parameter distributions) and scale effects. This represents a powerful means of controlling for scale effects that are assumed within other modelling structures, including mixed logit. Specifically, the GMNL model represents variable scale effects separate to mean and standard deviation parameters for randomly-distributed explanatory variables. Due to the GMNL model's general form, more restrictive models such as mixed logit and multinomial logit can be represented as subsets of GMNL models within which the estimated scale parameter takes particular values.

In this paper, we estimate GMNL models of choices made by buyers and sellers of freight transport services in Sydney under a hypothetical road user charging system. The estimates from this model are then carried forward into a GMNL model of freight group decision-making structures, yielding estimates of the relative influence supply chain members have with respect to the attributes in the choice study. The results from this analysis are compared to the results found under a generalised mixed logit model. We demonstrate the potential gains in goodness-of-fit and changes in behavioural inference that can be reached through calibrating scale effects directly.

The discussion begins with an overview of the GMNL model in Section 2. Section 3 offers a description of the econometric group decision-making modelling structure that forms the centre of the analysis, minimum information group inference (MIGI). The empirical data are introduced in Section 4, followed by the empirical analysis in Section 5. Section 6 concludes with a discussion of the implications of the use of the GMNL model within independent and interdependent group choice applications.

2. Methodology

2.1 Models Allowing for Preference Heterogeneity

Let U_{ntj} denote the utility of alternative *j* perceived by respondent *n* in choice situation *t*. U_{ntj} consists of two components, a modelled component V_{ntj} and an unobserved component ε_{nsj}, such that

$$U_{ntj} = V_{ntj} + U_{ntj} \tag{1}$$

As is common practice, we assume the modelled component of utility to be represented as a linear relationship of *k* attributes, *x*, related to each of the *j* alternatives and corresponding parameters weights such that

$$U_{ntj} = \sigma_n \sum_{k=1}^{K} \beta_{nk} x_{ntjk} + \varepsilon_{ntj} \tag{2}$$

where β_{nk} represents the marginal utility or parameter weight associated with attribute *k* for respondent *n* and the unobserved component, ε_{ntj} is assumed to be independently and identically (IID) extreme value type 1 (EV1) distributed. σ_n represents a scale factor that is typically normalised to one in most applications. As well as containing information on the levels of the attributes, *x* may also contain up to *J*-1 alternative specific constants (ASCs) capturing the residual mean influences of the unobserved effects on choice associated with their respective alternatives; where *x* takes the value 1 for the alternative under consideration or zero otherwise.

The utility specification in Equation (2) is flexible in that it allows for the possibility that different respondents may have different marginal utilities for each attribute being modelled. Such differences are accounted for in the mixed multinomial logit (MMNL) model by allowing one or more parameter to be specified as

$$\beta_{nk} = \bar{\beta}_k + \eta_k z_{nk} \tag{3}$$

where $\bar{\beta}_k$ represents the mean or some other measure of central tendency for the distribution of marginal utilities held by the sampled population and η_k represents a deviation from the mean (or other measure of central tendency) parameter and z_{nk} an individual specific (set of) draw(s) from some predefined distribution (e.g., $z_{nk} \sim N(0,1)$).

Given that the location for z_{nk} is unknown for any specific individual, it is necessary to take multiple pseudo random or quasi-random draws for each individual from z_{nk} for each individual decision maker during estimation. For this reason, the parameter weights given in Equation (3) are typically referred to as random parameters.

2.2 Models Allowing for Scale Heterogeneity

The typical normalization of σ_n to one in Equation (2) fails to formally recognize the possibility of scale heterogeneity, although models allowing for randomly distributed ASCs or error components do account for scale heterogeneity in a limited sense. Models allowing for randomly distributed ASCs are equivalent to allowing for heteroskedastic error terms with one interpretation being that this heteroskedasticity represents different scale across individuals. Similarly, error components may also be interpreted as the modeling of different scale across sampled individuals as the estimated parameter estimates are the standard deviation parameters linked directly to the unobserved influences of choice. Unfortunately, randomly distributed ASCs may appear in only *J*-1 alternatives and whilst multiple error component terms may appear in all *J* alternatives, any given error component may only be associated with *J*-1 of the modelled alternatives. As such, randomly distributed ASCs and error components apply different scale weights to each of the alternatives. This is strictly not the same as σ_n which impacts upon all *J* alternatives equally. As such, differences in scale across individuals cannot adequately be captured by the MMNL model as the scale differences in this model are not only captured across individuals, but simultaneously across individuals and (subsets) of alternatives.

To accommodate both scale and preference heterogeneity, Keane (2006) proposed the generalised multinomial logit (GMNL) model. First operationalised by Fiebig et al. (2010) and subsequently by Greene and Hensher (2010), the marginal utility for attribute *k* for the GMNL may be represented as Equation (4).

$$\beta_{nk} = \sigma_n \bar{\beta}_k + \gamma \eta_{nk} + \left(1-\gamma\right) \sigma_n \eta_{nk}, \tag{4}$$

where γ takes any value between 0 and 1 and where

$$\sigma_n = \mathrm{e}^{(\bar{\sigma}+\tau v_n)}. \tag{5}$$

In Equation (5), $\bar{\sigma}$ denotes a mean parameter of scale variance, τ a parameter of unobserved scale heterogeneity and v_n a standard normal distribution representing the unobserved scale heterogeneity.

Ignoring σ_n for the present, in the extreme case where γ takes the value 0, Equation (4) will collapse to

$$\beta_{nk} = \sigma_n\left(\bar{\beta}_k + \eta_{nk}\right), \tag{6}$$

suggesting that scale impacts equally upon both the mean (or central location) and standard deviation (or spread) parameters. Fiebig et al. (2010) refer to this model as GMNL2. At the other extreme, when γ equals 1, Equation (4) collapses to

$$\beta_{nk} = \sigma_n\bar{\beta}_k + \eta_{nk}, \tag{7}$$

suggesting that scale impacts only upon the mean (or central location) parameter. Fiebig et al. (2010) refer to this model as GMNL1. Values of γ between 0 and 1 suggest that scale impacts both the mean (or central location) and standard deviation parameters but to different extents.

Returning to σ_n, if σ_n is estimated to take the value 1, then the marginal utilities obtained from the model will collapse to the MMNL estimates given in Equation (3). If all η_{nk} simultaneously equal 0, then the model collapses to a scaled version of the MNL model (which Fiebig et al. (2010) refer to as the SMNL model), such that the marginal utilities obtained from the model are

$$\beta_{nk} = \sigma_n\bar{\beta}_k, \tag{8}$$

whilst if $\sigma_n = 1$ and all $\eta_{nk} = 0,$ then the model collapses to the MNL model.

2.3 Operationalising the GMNL Model

To estimate the GMNL or any of its restricted forms, maximum simulated likelihood estimation is used. In estimating the model however, a number of difficulties must first be overcome. Firstly, both Fiebig et al. (2010) and Greene and Hensher (2010) note that $\bar{\sigma}$ and σ_n in Equation (5) cannot be separately identified. Under the assumption that scale heterogeneity will be lognormally distributed and ignoring preference heterogeneity for the present, Fiebig et al. (2010) and Greene and Hensher (2010) both argue that

$$E\left[\sigma_n^2\right] = e^{\left(\bar{\sigma}^2+\frac{\tau^2}{2}\right)}. \tag{9}$$

In order for the model to be identified, it is necessary to normalise $E\left[\sigma_n^2\right]=1.$ In order to accomplish this normalisation, both Fiebig et al. (2010) and Greene and Hensher (2010) set $\bar{\sigma}=\frac{\tau^2}{2}$ such that Equation (5) becomes

$$\sigma_n = \mathrm{e}^{\left(\frac{-\tau^2}{2}+\tau v_n\right)}. \tag{10}$$

To ensure that scale remains positive, the model is fit in terms of λ such that

$$\tau = \mathrm{e}^{(\lambda)}, \tag{11}$$

where λ is unrestricted.

In estimation, depending on the estimates of λ and in turn τ, extremely large values of σ_n can occur depending on the values drawn from v_n. When such large values are observed, software overflows may occur and the estimator becomes unstable. As such, rather than use a standard normal distribution for v_n, Fiebig et al. (2010) employ truncated standard normal distribution with truncation at ±2. In taking this approach, any draw from outside this range is rejected and a new draw taken in its place. Rather than use a truncated standard normal distribution with an acceptance or rejection of the random parameter draw approach, Greene and Hensher (2009) propose a method to directly restrict the values of v_n to be between ±1.96. This is achieved by setting $v_{nr}=\Phi^{-1}\left[0.025+0.95U_{nr}\right]$ where the value of v_n for the r^{th} draw is calculated from the inverse of the standard normal cumulative distribution function, $\Phi^{-1}[.]$ given a random draw from a standard uniform distribution bounded by 0 and 1. Assuming that draw r from U_{nr} is 0, then the probability is transformed to 0.025. At the other bound, a draw of 1 for U_{nr} corresponds to a probability of 0.975. As such, $\Phi^{-1}[.]$ will be naturally bounded at ±1.96. For the current paper, we utilize the approach suggested by Greene and Hensher (2009).

Finally, in order to impose the limits on γ, γ is reparameterised in terms of α such that

$$\gamma = \frac{e^{\alpha}}{1+e^{\alpha}}, \tag{12}$$

where α is unrestricted in both sign and magnitude. This ensures that γ will be bounded within the 0-1 range.

3 Minimum Information Group Inference

Predominant empirical constraints in urban freight studies led to the investigation of alternative ways to make behavioural inferences for interdependent decision makers within discrete choice analysis. The minimum information group inference (MIGI) method was identified within the study yielding the empirical data analysed herein to obtain desired behavioural estimates. MIGI enables the analyst to model the influence structures within decision-making groups, such as the freight transport buyer-seller dyads of key interest within this research application (see Hensher and Puckett (2005) and Puckett *et al*. (2006) for a detailed justification), by inferring the effects of interactivity based on the stated willingness of respondents to *concede toward* the preferences of the other member of their respective sampled groups.

MIGI models use SC experiments that augment the standard SC format to incorporate an interactive setting within an experiment that is administered to an individual respondent. As with interactive agency choice experiments (IACEs – see Brewer and Hensher, 2000), each respondent within a sampled group is given a set of identical choice sets. The resulting choice observations are coordinated across respondents and analysed to infer the effects of interdependency among the sample of interest, without requiring direct interaction among respondents. That is, the effects of interactive agency are inferred *ex post*, by projecting group outcomes based upon the preference rankings given by respondents within an algorithm designed to coordinate these rankings.

Similar to an IACE, MIGI experiments are framed in terms of an interactive setting, within which respondents are asked to indicate their preferences among the given alternatives. Specifically, MIGI experiments prompt respondents to indicate how they would rank the alternatives if they had to attempt to reach agreement with the other member(s) of the sampled group. Importantly, the ranking process includes the option of denoting an alternative as unacceptable, to avoid inferring agreement outcomes that would not likely be observed under direct interaction. In other words, allowing respondents to indicate that they would not concede toward other respondent(s) to a specified degree within a given choice set preserves the potential to infer non-agreement outcomes for a sampled group.

Unlike IACEs, MIGI does not involve an iterative process in which respondents are presented with information about the preferences of the other respondent(s) in the group and given the opportunity to revise their preferences. Rather, the influence of each respondent in a sampled group is inferred through the coordination of the preference rankings given by each respondent in a particular sampled group for a particular choice set. Influence is hypothesized to be represented within the preference rankings, in that respondents who are relatively more willing to accept less favourable alternatives are modelled as though they would be willing to offer relatively more concession within a direct interaction with the other group member(s). That is, the preference rankings themselves are indicative of the levels of concession the respondent would offer when interacting with the other member(s) of the group.

Utilising the preference rankings of each respondent in a sample group, group preferences and influence structures are estimated through “power models”. As shown below, the power models offer a means of quantifying group influence structures consistent with the manner proposed by Dosman and Adamowicz (2003). MIGI analysis builds on the econometric structure offered by Dosman and Adamowicz, enabling the analyst to estimate attribute-specific measures of influence. This is an important behavioural step, in that it allows the analyst to gauge the degree to which each type of decision maker holds influence over each attribute in consideration by the group. This proposition should be tested rather than assume that one type of decision maker holds the same degree of relative influence over all aspects of the decision or relationship in question.

The first stage of econometric analysis in MIGI modelling involves the estimation of individual preferences for each agent type. Independent preferences are established by modelling the choices of the most-preferred alternative for each respondent as a function of the attribute levels for each alternative and the contextual effects corresponding to each choice set. That is, despite the interdependent nature of the experiment, standard independent preferences are not only informative outputs on their own, but also offer a basis for comparison with group preferences.

The behavioural process assumes that each agent *q* acts as if he or she is a utility maximiser when choosing a most-preferred alternative *j* in a choice set *p* faced by all members of a sampled group *g*. The base utility expressions (*i.e.*, without any interaction effects or direct covariate effects) are of the general form:

$$U_{qj} = \alpha_j + \boldsymbol{\beta}'_{\mathbf{qk}} * \mathbf{x}_{\mathbf{jk}} + \varepsilon_{qj}, \tag{13}$$

where U_{qj} represents the utility derived by *q* from *j*, α_j represents an alternative-specific component of utility (if the design includes either labelled alternatives, or if one wishes to distinguish structurally between the reference alternative and stated choice alternatives), $\boldsymbol{x}_{jk}$ is a vector of design attributes associated with agent *i* and alternative *j*, $\boldsymbol{\beta}_{qk}$ is the corresponding vector of marginal (dis)utility parameters (treated as random parameters if allowed to vary across *q*), α_j is an alternative-specific constant, and ε_{qj} represents the (potentially individual-specific) unobserved effects.

At this point in the analysis, independent utility estimates have been obtained for each respondent in the sample, and a range of group choices have been projected for each choice set commonly faced by each group. With this information, group preferences may be estimated using a procedure that is consistent with empirical modelling structures that can be utilised for the analysis of interactive agency SC data or RP data (Dosman and Adamowicz, 2003; Hensher and Knowles, 2007). That is, for a given choice set, the projected chosen alternative of the group is compared to the unchosen alternatives in order to estimate a vector of attribute-specific power measures, $\boldsymbol{\tau}_{qk}$.

To accomplish this, estimates of the individual preference parameters for respondents in a group are carried forward as constant exogenous terms into the following *power model* and multiplied by the corresponding attribute levels for each of the *K* attributes in each alternative *j* in choice set *p* faced by all respondents *q* in group *g*. For each simulated group interaction *gp*, the alternative designated as the choice is the group choice projected using a choice coordination algorithm. The previously-estimated independent marginal utilities derived by each *q* in each *j*, the vector of attribute levels in each alternative $\boldsymbol{x}_{jk}$ and any covariates of interest are the exogenous variables used to calculate the vector $\boldsymbol{\tau}_{\mathbf{qk}}$, which, along with any alternative-specific constants are the only free parameters in the model. Whilst the most general two-agent case is offered here, this calculation can be augmented through the inclusion of interaction terms and additional respondents:

$$\begin{aligned}
U_{11} &= \alpha_{11} + (\boldsymbol{\tau}_{\mathbf{qk}} * \boldsymbol{\beta}_{\mathbf{qk}})' * \mathbf{x}_{\mathbf{1k}} + ((\mathbf{1} - \boldsymbol{\tau}_{\mathbf{qk}}) * \boldsymbol{\beta}_{\mathbf{q'k}})' * \mathbf{x}_{\mathbf{1k}} + \varepsilon_{11} \\
&\ldots \\
U_{1J} &= \alpha_{1J} + (\boldsymbol{\tau}_{\mathbf{qk}} * \boldsymbol{\beta}_{\mathbf{qk}})' * \mathbf{x}_{\mathbf{1k}} + ((\mathbf{1} - \boldsymbol{\tau}_{\mathbf{qk}}) * \boldsymbol{\beta}_{\mathbf{q'k}})' * \mathbf{x}_{\mathbf{Jk}} + \varepsilon_{1J} \\
&\ldots \\
U_{JJ} &= \alpha_{JJ} + (\boldsymbol{\tau}_{\mathbf{qk}} * \boldsymbol{\beta}_{\mathbf{qk}})' * \mathbf{x}_{\mathbf{Jk}} + ((\mathbf{1} - \boldsymbol{\tau}_{\mathbf{qk}}) * \boldsymbol{\beta}_{\mathbf{q'k}})' * \mathbf{x}_{\mathbf{Jk}} + \varepsilon_{JJ},
\end{aligned} \tag{14}$$

where U_{jm} is the estimated utility the group *g* derives from the joint choice of alternative *j* by agent *q* and alternative *m* by agent *q'* in simulated group interaction *gp*, α represents an alternative-specific utility component for the joint choice alternative, $\boldsymbol{\tau}_{qk} * \boldsymbol{\beta}_{qk}$ represents a vector of the product of relative influence measures for a focal agent type and the independent marginal utility derived by q for attribute k in j, $\boldsymbol{x_{jk}}$ represents the vector of levels of each k present in j, $\boldsymbol{((1-\tau_{qk})*\beta_{q'k})'}$ represents a vector of the product of relative influence measures for the other agent $\boldsymbol{(1-\tau_{qk})}$ and the independent marginal utility derived by q' for k in m, $\boldsymbol{x_{mk}}$ represents the vector of levels of each k present in m, and ε_{jm} represents the unobserved effects for the joint choice alternative.

The final decision of a group should involve either agreement across all members, or impasse, which is likely to result in a continuation of the *status quo*. When restricting the analysis to cases of agreement or impasse, the model reduces to the subset of Equation (14) in which the choices made by both decision makers are coincident (*i.e.*, each agent chooses the same alternative j). We refer to this context as group equilibrium, under which one can estimate influence structures under cooperative and non-cooperative equilibrium outcomes.

The econometric analysis focuses on a pair of power models that reflect the relative power structure present when a given agent type (herein a transport or a shipper) offers concession toward the preferences of the other agent. For example, in the *transporter concession* power model, we present estimates of the influence structure present when transporters offer a degree of concession they state they are willing to offer toward the first preferences of shippers. Likewise, in the *shipper concession* power model, we present estimates of the influence structure present when shippers offer a degree of concession they state they are willing to offer toward the first preferences of transporters. Analysing influence structures in the two most extreme cases of concession, the preference data allow us to infer (*i.e.*, when decision makers are willing to accept the first preference of the other decision maker in their respective groups) estimates of a range of relative power, within which one would expect to find corresponding point estimates if direct interaction between agents could be observed.

The power measures for agents q ($\boldsymbol{\tau_{qk}}$) and q' ($\boldsymbol{1-\tau_{qk}}$) sum to unity for each attribute k, making comparisons of influence across agent types straightforward. If the two power measures are equal for a given attribute k (i.e., $\tau_{qk} = (1 - \tau_{qk}) = 0.5$), then group choice equilibrium is not governed by a dominant agent with respect to attribute k. In other words, regardless of the power structure governing other attributes, agent types q and q' tend to reach perceptively fair compromises when bridging the gap in their preferences for k. If the power measures are significantly different across agent types (e.g., $\tau_{qk} >> (1 - \tau_{qk})$), then τ_{qk} gives a direct measure of the dominance of one agent type over the other with respect to attribute k, as τ_{qk} increases, so does the relative power held by agent type q over q' for k.

For example, in a freight distribution chain, the power measures may reveal that one agent type tends to get its way with regard to monetary concerns, whereas the other agent type tends to get its way with regard to concerns for levels of service. These relationships can be examined further within subsets of agent groups (by decomposition of the random parameter specification of $\boldsymbol{\tau_{qk}}$), in order to reveal deviations from the inferred behaviour at the sample level that may be present for a particular type of relationship.

It is important to note that the range of power measures is unbounded. That is, the only constraint on the power measures is that they sum to one across members of a group. Hence, it is possible to observe power measures either less than zero or greater than one. This is straightforward, in that a (0,1) bound is excessively restrictive for group decision making, especially for cases of trade-offs across fixed attribute bundles. The limited set of pre-specified trade-offs may make it necessary for a decision maker to offer more than requested with respect to one attribute in order to reach agreement on an alternative. Therefore, one may observe a tendency for a given type of decision maker to offer greater concession toward the preferences of another type of decision maker for a given attribute than the initial discrepancy in preferences between the decision makers, resulting in an estimated power measure outside of the (0, 1) range.

The distribution of power measures across a given set of decision makers can be decomposed, and hence explained, by both objective and subjective descriptors of the relationship between members of groups within a sample. The mixed logit model, implemented within MIGI analysis, allows the analyst to model relative influence with respect to a given attribute as a function of characteristics within the relationship between interdependent decision makers. Objective descriptors include tangible factors such as measures of market power and the length of the relationship, whereas subjective descriptors include attitudinal statements about the importance of elements within the relationship and the effectiveness of the relationship in achieving those elements.

The specific algorithm for coordinating the choices of group members within the power models is straightforward. Within the power model of concession by agents of type *q*, the group choice is specified as the first preference of the respondent of type *q*' if the respondent of type *q* stated that he or she was willing to accept that alternative as a group choice outcome. If the alternative is unacceptable to the respondent of type *q*, the group choice is specified as a non-cooperative outcome; in this empirical exercise, the non-cooperative case is represented by maintaining the *status quo* (*i.e*., the RP alternative). This process is repeated for all power models representing the relative concession a decision maker is willing to offer toward the preferences of another decision maker. To estimate the relative power measures $\boldsymbol{\tau_{qk}}$ in each concession model, group choice observations are projected for each choice set (including choice set *p*, for which the group choice is designated as *3*), with the independent utility estimates $\boldsymbol{\beta_{qjk}}$ and $\boldsymbol{\beta_{q'mk}}$ carried forward from the first modelling stage, and with the attribute levels $\mathbf{x_{jk}}$ and $\mathbf{x_{mk}}$ set equal to those faced in choice set *p* for both choice observations.

The power measures that result from estimating the group choice outcome utility functions highlight the process of concession required when agents with non-coincident preferences attempt to reach group choice equilibrium. That is, while the choice coordination algorithm is the mechanism by which group choice is projected in the model, the information that seeds the algorithm in turn allows the analyst to project the degree to which one agent type tends to get its way for a given attribute. Ultimately, although the analyst does not directly observe the interaction of two agents, the analyst has the ability to infer the process by which differing preferences converge toward group preference equilibrium.

4 Empirical Data

A 2004 study of road freight stakeholders in Sydney, Australia centred on capturing information about independent and interdependent preferences of carriers and shippers in the presence of a (hypothetical) distance-based road pricing system. Consistent with other freight studies, the predominant empirical constraints in the study were: (a) a small population from which to draw; (b) a limited research budget; and (c) difficulties in gaining the cooperation of freight stakeholders. A limited number of agents to sample (i.e., freight firms and their clients under contracts involving urban goods movement) requires optimisation on two counts: (1) recruiting a sufficient proportion of the population for the sample and (2) obtaining a sufficient number of choice observations for each respondent. A minimum information group inference (MIGI) experiment was chosen to allow for a relatively larger sample than a stated choice experiment involving direct interaction between sampled group members due to the relative ease of recruiting participants; that is, no temporal coordination of respondents was required.

The empirical procedure began by administering the experiment to representatives of freight firms. Centred on a CAPI survey with a d-optimal experimental design (discussed in

Puckett *et al*., 2007), the MIGI experiment involved three distinct procedures: (1) non-stated-choice questions intended to capture the relevant deliberation attributes and other contextual effects; (2) choice menus corresponding to an interactive (*i.e*., freight-contract-based) setting; and (3) questions on the attribute processing strategies enacted by respondents within each choice set.

After a sampled respondent from a freight firm completed the survey, a client of a freight firm matching the classification offered by the respondent was recruited and given a survey involving the identical series of choice sets faced by the corresponding freight firm.

The levels and ranges of the attributes were chosen to reflect a range of coping strategies under a hypothetical distance-based road user charging regime. The reference alternative within each choice set for respondents from freight firms is created using the details specified by the respondent for the recent freight trip. In all cases except for the variable charges, the attribute levels for each of the SC alternatives are pivoted from the levels of the reference alternative, as detailed below. The levels are expressed as deviations from the reference level, which is the exact value specified in the corresponding non-SC questions, unless noted:

1. **Free-flow time**: -50%, -25%, 0, +25%, +50%
2. **Slowed-down time**: -50%, -25%, 0, +25%, +50%
3. **Waiting time at destination**: -50%, -25%, 0, +25%, +50%
4. **Probability of on-time arrival**: -50%, -25%, 0, +25%, +50%, with the resulting value rounded to the nearest 5% (*e.g.*, a reference value of 75% reduced by 50% would yield a raw figure of 37.5%, which would be rounded to 40%).
5. **Fuel cost**: -50%, -25%, 0, +25%, +50% (representing changes in fuel taxes of -100%, -50%, 0, +50%, +100%)
6. **Distance-based charges**: -50%, -25%, 0, +25%, +50% around a base of 50 percent of the fuel cost (i.e., 100 percent of fuel taxes).

Respondents were asked to assume that, for each of the choice sets given, the same goods need to be carried for the same client, subject to the same constraints faced when the reference trip was undertaken. The specific choice task on the initial screen is, 'If your organization and the client had to reach agreement on which alternative to choose, what would be your order of preference among alternatives?' Respondents are asked to provide a choice for every alternative. The available options for each alternative are: (Name of the alternative) is: My 1st choice; My 2nd choice; My 3rd choice; Not acceptable. At least one of the alternatives must be indicated as a first choice, which was not found to be restrictive, given that the reference alternative represents the *status quo*, which was clearly acceptable in the market.

The resulting estimation sample, after controlling for outliers and problematic respondent data, includes 114 transporters and 108 shippers. The transporters response rate was 45% whereas that of the shippers was 72%.

5 Empirical Results

5.1 Independent Preference Estimates

Our empirical exercise centres on a comparison of MIGI group influence measures when accounting for scale and preference heterogeneity within the GMNL model versus the mixed logit estimates found in Hensher and Puckett (2008). As discussed in Section 3, MIGI involves a two-stage process that begins with the estimation of independent preferences for each agent type within the model (i.e., transporters and shippers). The model selected in this application includes six attributes (and transformations of attributes) specified as random parameters, distributed triangularly with spread equal to the mean: total travel time, waiting time, the probability of on-time arrival, the freight rate, the proportion of variable charges within the freight rate, and fuel cost. The data were rank-exploded, yielding 743 observations for transporters (from 114 respondents facing four choice sets of three alternatives each) and 1550 observations for shippers (from 108 respondents facing eight choice sets of three alternatives each).

Table 1 summarises the model outputs relating to the preferences of transporters and shippers:

Table 1: Independent Agent GMNL Models

	Transporters		Shippers	
	Par.	(*t*-ratio)	Par.	(*t*-ratio)
Random Parameters				
Total Travel Time	-0.010	(-4.54)	-0.054	(-38.13)
Waiting Time	0.007	(1.30)	-0.028	(-14.46)
Probability of On-Time Arrival	0.069	(7.20)	0.075	(23.65)
Freight Rate	0.017	(7.96)	-0.070	(-76.05)
Variable Charge/Freight Rate	-0.185	(-5.50)	-0.037	(-4.03)
Fuel Cost	-0.030	(-9.34)	-0.021	(-13.31)
Non-Random Parameters				
Constant (RP)	0.846	(5.49)	0.671	(6.57)
Constant (SP1)	0.006	(0.05)	0.164	(1.49)
Variance Parameter in Scale				
Variance Parameter in Scale (τ)	1.213	(6.81)	1.000	(23.22)
Weighting Parameter Gamma				
Gamma Parameter (γ)	0.509	(2.79)	0.500	(6.81)
Sigma Parameters				
Sample Mean	0.808	-	0.870	-
Sample Std. Dev.	0.886	-	0.779	-
Model Fits				
LL(ASC)	-631.297		-1291.633	
LL(β)	-526.618		-921.067	
Pseudo ρ^2(ASC)	0.166		0.287	
Number of Respondents	114		108	
Number of Observations	743		1550	

Shippers appear more sensitive to travel-related attributes than transporters. This is an interesting behavioural result that may underscore the distinct roles that freight transport activity represents for customers versus providers. At a fundamental level, transporters are in the business of travelling (whether in free-flow or slowed-down conditions) and waiting at loading and unloading points; hence, whilst marginal improvements in travel efficiency are likely to increase utility, the actual activity of carrying or waiting with goods offers less disutility than for customers who are paying for this activity (and who are unable to utilise the goods being carried until they are no longer being carried). Indeed, transporters not only show a much lower mean marginal disutility to travel time (-0.1 versus –0.54 for shippers), but also demonstrate some possible positive utility of waiting time at the levels present in the survey (0.007 with a *t*-value of 1.3, versus –0.028 for shippers). This is sensible if transporters are being paid for the time spent waiting or if the quantity of waiting time is not significant enough to disturb subsequent activity. Of course, for no attribute are the roles more diametrically opposed than for the freight rate, with shippers showing a larger disutility for a marginal dollar paid than the utility gained by transporters for that same dollar (0.017 for transporters versus –0.07 for shippers).

Transporters and shippers demonstrate quite similar preferences for improving reliability (parameter of 0.069 for transporters versus 0.075 for shippers). This may indicate that transporters and shippers could have relatively low barriers to working together to enact strategies to improve the reliability of freight travel relative to other attributes of distribution strategies.

Transporters reveal stronger sensitivities than shippers to direct operating costs of travel, which is intuitive. Transporters are much more sensitive to the magnitude of distance-based charges relative to the freight rate than shippers (mean marginal disutility of –0.185 for transporters versus –0.037 for shippers). This is consistent with shippers' relatively strong sensitivities to travel characteristics if they view the charges as offering sufficiently improved levels-of-service (i.e., value for money). Conversely, for transporters, any charges that cannot be passed along to customers may not represent the same improvement. Fuel cost offers disutility to transporters and shippers, the latter of whom may acknowledge the correlation between fuel cost and both expected freight rates and travel times (i.e., *ceteris paribus*, a relatively quick trip in free-flow conditions should take less time, burn less fuel and hence cost less than other trips). Still, the direct disutility for transporters of spending money on fuel, along with corresponding operating costs relating to trips under lower fuel efficiencies, is connected to higher disutilities than for shippers.

Turning to the functional form of the GMNL model, the models of transporter and shipper preferences yield similar gamma parameters at or near 0.5. Returning to Equation (4), these estimates imply that for both transporters and shippers scale impacts the mean and standard deviation estimates in different ways (but in the same functional form across the two models). As such, the flexibility of the GMNL model in capturing information on scale heterogeneity may offer significant improvements in representing transporter and shipper choice behaviour above alternative model specifications.

5.2 Shipper Concession Model

We now turn to model outputs from the power models discussed in Section 3. The *shipper concession* and *transporter concession* models represent our estimated outer bounds of ranges of relative influence held by transporters and shippers over the attributes within the empirical study. Each model projects the group choice for a given choice set as either: (a) the first preference of the respondent toward whom concession is offered by the focal agent type, if the focal agent stated he or she is willing to accept that alternative as the group choice or (b) the RP alternative, if the focal agent was unwilling to accept the other decision maker's first preference as the group choice. For example, within the shipper concession model, the group choice for a given choice set is projected as the first preference of the transporter if the shipper stated he or she is willing to accept that alternative as the group choice. If the shipper stated that the alternative is unacceptable, no new strategy would be guaranteed to be a consensus choice, and hence the *status quo* (*i.e*., the RP alternative) would be maintained.

The attribute-specific power measures resulting from each of these models reflect the relative concession each decision maker is willing to offer. That is, the models represent the degree to which each type of decision maker is willing to accommodate the preferences of the other decision maker when their first preferences do not coincide. This is represented empirically through power measures that are considered in reference to 0.5, a value that indicates that each decision maker is willing to offer the same level of concession with respect to the attribute in question. Values significantly above (below) 0.5 indicate that transporters (shippers) hold significant power relative to shippers (transporters), and hence are likely to achieve group choice equilibria that preserve a relatively greater proportion of their own preferences.

Tables 2 and 3 summarise the results of the shipper concession model:

Table 2: Shipper Concession Model

Random Parameters (Distributed Triangularly)		
	Value	t-ratio (for power measures, relative to 0 and 0.5, respectively)
Total Travel Time (Mean)	0.936	6.92, 3.22
Total Travel Time (Std. Dev.)	0.936^	6.92
Variable Charge/Freight Rate (Mean)	1.701	2.85, 2.01
Var. Charge/Freight Rate (Std. Dev.)	2.720	2.02
Prob. of On-Time Arrival (Mean)	2.716	4.72, 3.85
Prob. of On-Time Arrival (Std. Dev.)	2.716^	4.72
Non-Random Parameters		
Constant (RP)	1.454	6.02
Constant (SP1)	-0.179	-0.66
Waiting Time	0.839	3.35, 1.35
Freight Rate	0.968	22.62, 10.94
Fuel Cost	1.327	9.15, 5.71
Variance Parameter in Scale		
Variance Parameter in Scale (τ)	0.769	3.75
Weighting Parameter Gamma		
Gamma Parameter (γ)	0.691	0.76
Sigma Parameters		
Sample Mean	0.924	-
Sample Std Dev.	0.456	-
Model Fits		
LL(ASC)	-470.21	
LL(β)	-255.02	
Pseudo ρ^2	0.458	
Number of Sampled Pairs	107	
Number of Observations	428	

^Spread constrained as equal to the mean

Table 3: Descriptive Statistics of Estimated Individual-Specific Power Measures (Shipper Concession, GMNL)

	Travel Time	On-Time Arrival	Variable Charges
Mean	0.86	2.53	1.56
Std. Dev.	0.36	0.90	0.71
Minimum	0.19	1.11	-0.39
Maximum	2.60	7.46	4.45

The shipper concession model reveals that shippers are potentially willing to accommodate the preferences of transporters with respect to many attributes within the analysis. The power measures that infer the greatest influence for transporters relates to the probability of on-time arrival, waiting time, the freight rate and fuel cost. Implications with respect to on-time arrival may be obscured by the close magnitudes of independent preferences across the two groups, however. It is interesting to observe the relative willingness to accommodate transporters' preferences over fuel cost, as optimising fuel consumption would be an objective directly within transporters' expertise and motivations. Travel time and variable charges involve a diverse range of power structures under concession by shippers; that is, some, but not all, shippers are willing to accommodate the preferences of transporters with respect to travel time and variable charges.

The estimated gamma parameter implies that the model form approaches the GMNL2 form as identified by Fiebig *et al*. (2010). That is, scale effects appear to have impacted the mean and standard deviation parameters, although not quite equally.

We can now compare the estimated distributions of power measures in the shipper concession model with those from the mixed logit model in Hensher and Puckett (2008), as shown in Table 4:

Table 4: Descriptive Statistics of Estimated Individual-Specific Power Measures (Shipper Concession, Mixed Logit)

	Travel Time	On-Time Arrival	Freight Rate	Variable Charges	Fuel Cost
Mean	0.14	1.10	0.57	2.82	2.05
Std. Dev.	1.25	0.29	0.10	0.85	1.10
Minimum	-8.63	0.04	0.37	-1.31	-1.26
Maximum	1.17	1.93	0.98	4.00	8.49

Beyond the limitation that the original power model did not include waiting time, some important distinctions emerge across the two models. Firstly, the estimated ranges of power values are commonly much larger in the mixed logit case. Secondly, the specific behavioural implications of the mixed logit shipper concession model are not coincident with those from the GMNL model. Across the two models, shippers are represented as offering strong concession to the preferences of transporters with respect to on-time arrival, variable charges and fuel cost. However, the degree of relative power held by shippers over travel time and the freight rate appears to be much smaller in the GMNL model. Furthermore, after accounting for scale heterogeneity, the GMNL model does not identify the same degree of heterogeneity in the range of power measures. That is, incorporating scale heterogeneity in the model leads to a restricted range of attributes over which there appears to be heterogeneity in relative influence across groups; in the GMNL model, no significant heterogeneity was identified with respect to power over the freight rate or fuel cost.

5.3 Transporter Concession Model

To make inferences with respect to the power structures between transporters and shippers without directly observing their interactions, the analyst can contrast the results from the shipper concession model with those from the transporter concession model (*i.e.*, the model accounting for the degree to which transporters are willing to accommodate the first preferences of shippers). We now turn to the results of the GMNL transporter concession model, as summarized in Tables 5 and 6:

Table 5: Transporter Concession Model

Random Parameters (Distributed Triangularly)		
	Value	***t*-ratio (for power measures, relative to 0 and 0.5, respectively)**
Total Travel Time (Mean)	-0.756	-4.79, -7.95
Total Travel Time (Std. Dev.)	1.949	4.22
Variable Charge/Freight Rate (Mean)	0.809	1.31, 0.50
Var. Charge/Freight Rate (Std. Dev.)	3.566	2.64
Fuel Cost (Mean)	-0.604	-5.18, -9.54
Fuel Cost (Std. Dev.)	0.604^	5.18
Non-Random Parameters		
Constant (RP)	1.256	4.24
Constant (SP1)	-0.665	-1.77
Waiting Time	-0.597	-2.43, -4.79
Prob. of On-Time Arrival	-0.678	-4.86, -4.33
Freight Rate	-0.103	-4.69, -27.43
Variance Parameter in Scale		
Variance Parameter in Scale (τ)	0.546	2.15
Weighting Parameter Gamma		
Gamma Parameter (γ)	0.436	0.41
Sigma Parameters		
Sample Mean	0.962	-
Sample Std Dev.	0.462	-
Model Fits		
LL(ASC)	-470.21	
LL(β)	-284.99	
Pseudo ρ^2(ASC)	0.394	
Number of Sampled Pairs	107	
Number of Observations	428	

^Spread constrained as equal to the absolute value of the mean

Table 6: Descriptive Statistics of Estimated Individual-Specific Power Measures (Transporter Concession, GMNL)

	Travel Time	Variable Charges	Fuel Cost
Mean	-0.77	0.79	-0.59
Std. Dev.	0.56	0.65	0.18
Minimum	-2.90	-1.95	-1.36
Maximum	0.51	2.14	-0.29

The transporter concession model reveals that transporters are potentially willing to accommodate the preferences of shippers with respect to every attribute, with the key exception of variable charges. The breadth of attributes over which transporters are willing to offer concession is supported by a strong magnitude of concession. That is, not only are transporters willing to offer strong concession towards shippers' preferences on average for all attributes except for variable charges (i.e., means of distributions and fixed coefficients of power measures below zero), but the estimated power measures are generally in the range reflecting total concession for these attributes. Variable charges, on the other hand, are an attribute over which transporters appear highly resistant to offering concession. Transporters' stated willingness to concede demonstrates that transporters are not generally willing to increase the proportion of variable charges they pay relative to the freight rate in response to the preferences of shippers.

The estimated gamma parameter implies that the model form approaches the GMNL2 form as identified by Fiebig *et al*. (2010). That is, scale effects appear to have impacted the mean parameters similarly to the standard deviation parameters.

We can now compare the estimated distribution of power measures in the transporter concession model with those from the mixed logit model in Hensher and Puckett (2008), as shown in Table 7:

Table 7: Descriptive Statistics of Estimated Individual-Specific Power Measures (Transporter Concession, Mixed Logit)

	Travel Time	On-Time Arrival	Freight Rate	Variable Charges	Fuel Cost
Mean	0.15	1.11	0.03	1.67	-0.12
Std. Dev.	1.01	0.09	0.33	0.42	0.00
Minimum	-5.00	0.80	-0.13	-2.23	-0.13
Maximum	2.35	1.58	0.74	2.51	-0.12

As with the shipper concession model, the estimated ranges of some power values (travel time and variable charges) are much larger in the mixed logit case, with some values well away from the unit interval. The behavioural implications across the GMNL and mixed logit models are generally consistent, as well, with on-time arrival being the one exception; in the GMNL model, transporters appear willing to offer concession to the preferences of shippers. However, given the similar independent sensitivities to on-time arrival for transporters and shippers, this may simply be a difficult attribute over which to identify relative power (i.e., both transporters and shippers have similar motivations to optimise with respect to on-time arrival). Consistent with the shipper concession model, accounting for scale heterogeneity results in a restricted set of power measures over which significant heterogeneity is identified; whilst the mixed logit model identifies heterogeneity in relative power across each attribute, the GMNL model does not identify significant heterogeneity with respect to power over on-time arrival or the freight rate.

5.4 Comparison of Results under Shipper Concession and Transporter Concession

Comparing the results from the shipper concession and transporter concession models enables inferences to be made about the range of power structures that are likely to be observed amongst transporters and shippers under variable charging. There are three main types of power structures that are likely to be observed at the variable level: relative power held by transporters, relative power held by shippers, and balanced power (either on average, with power depending upon relationship characteristics, or overall, with a general tendency for power to be balanced).

Across the GMNL concession models, two types of relationships appear to dominate. Transporters appear to hold strong power with respect to variable charges, regardless of the degree of concession offered by either type of decision maker. This result is consistent with the results from the mixed logit model. However, in the mixed logit model, transporters were represented as having strong power over on-time arrival probability, which is not the case in the GMNL model; the similar estimated independent sensitivities for transporters and shippers within the GMNL model imply a broader range of cooperative outcomes that could be observed for on-time arrival. The ranges of group-specific power measures indicate that transporters may hold at least some degree of relative power over decisions impacting travel time, as well.

Consistent with the mixed logit model, the GMNL model does not identify any particular attributes over which shippers are resistant to cooperating with transporters. Rather, waiting time, fuel cost, on-time arrival probability and the freight rate are identified by the GMNL power models as attributes over which a range of cooperative outcomes could be observed.

Ultimately, the GMNL power models suggest that policy measures centred on the implementation of variable charges are likely to impact urban goods movement mainly through the influence of the preferences of transporters. That is, despite the interdependent nature of urban goods movement, transporters appear to hold power over the response of supply chains to a variable charging system. The GMNL model places a clear focus on heterogeneity in group dynamics with respect to both variable charges and travel time. Hence, strategies involving optimisation with respect to the transporter’s preferences for variable charges may not only be enacted in distinct ways across types of decision-making groups, but the relative benefits obtained in terms of travel time also do not appear to be uniform across groups. This, along with the general willingness of transporters and shippers to accommodate the preferences of their partners with respect to waiting time, on-time reliability, fuel cost if offered sufficient value for money (i.e., through the freight rate) indicates opportunities for shippers to secure agreeable outcomes when opting for strategies that benefit transporters through preferences for variable charges.

6 Conclusions

The comparison of GMNL and mixed logit model results within an interdependent decision-making context demonstrate how behavioural implications can be a direct function of the role of scale within econometric models. Assuming any particular fixed scale structure could lead to policy implications that are counter to those arising from another assumed scale structure. Given the likelihood that assumptions about scale, which itself is unobserved within some models, may be arbitrary and unnecessarily restrictive, this result is worth further investigation within extant and future empirical applications. That is, there may be misleading policy outputs in both independent and interdependent applications that are a result of relationships between (misspecified) scale and preference estimates.

The use of a flexible structure such as the GMNL model allows us to re-examine behavioural relationships by breaking apart the impact of scale from preference estimates within sophisticated models that account for preference heterogeneity. It appears to be a worthwhile exercise to confirm previously derived behavioural results from other models within GMNL models to improve our confidence in a range of model outputs, including pivotal elements such as willingness-to-pay. Whilst the application discussed herein focuses on group influence structures, the implications are by no means limited to group decision-making.

Fortunately, the comparison of GMNL and mixed logit results in this case did confirm the relative power that transporters appear to hold over variable charges. Hence, despite the potential for misspecification bias in relation to scale effects, the mixed logit model did identify the leading role that transporters stand to play in group responses to variable road-user charging.

Beneficial research would include re-examining extant studies into preference heterogeneity, both within and outside of urban freight studies, and for studies of independent and interdependent decision makers, by accounting for scale heterogeneity explicitly. The GMNL model offers an empirically straightforward tool for accomplishing this, requiring little further analyst input than standard mixed logit models. Not only would it beneficial to identify whether scale itself plays a significant role in existing behavioural models, but it may also be critical to identify whether some degree of preference heterogeneity present (or absent) in existing models is actually an artefact of unidentified scale heterogeneity. In a given application, such potential misspecification may be vital to confirm, especially in cases where appropriate policy depends upon knowledge of the degree to which some individuals or groups may be impacted differently to the population, in general.

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