Journal of Transport Economics and Policy, Volume 45, Part 2, May 2011, pp. 197–222

Social Exclusion and the Value of Mobility

John Stanley, David A. Hensher, Janet Stanley, Graham Currie, William H. Greene, and Dianne Vella-Brodrick

Address for correspondence: John Stanley, Institute of Transport and Logistics Studies, The University of Sydney Business School, University of Sydney, NSW 2006 Australia (J.Stanley@itls.usyd.edu.au). David A. Hensher is at the Institute of Transport and Logistics Studies, The University of Sydney Business School, University of Sydney. Janet Stanley is at Monash Sustainability Institute, Monash University. Graham Currie is at the Institute of Transport Studies, Monash University. William H. Greene is at the Stern School of Business, New York University. Dianne Vella-Brodrick is at the School of Psychology, Psychiatry, and Psychological Medicine, Monash University.

This research was undertaken as part of Australian Research Council Industry Linkage Program Project LP0669046: 'Investigating Transport Disadvantage, Social Exclusion and Well Being in Metropolitan, Regional and Rural Victoria'. The industry partners are the Victorian State Government, Local Government from the fringes of Melbourne, the Brotherhood of St Laurence (a peak welfare organisation) and Bus Association Victoria, an industry association representing bus operators in Victoria. Thanks are also due to Alexa Delbosc for research input.

Abstract

This paper investigates factors likely to increase a person's risk of social exclusion, drawing on survey data specifically framed for this purpose. We use a generalised ordered logit model that accounts for observed and unobserved heterogeneity and derive the marginal effects for each influencing attribute. We find that people are less likely to be at risk of social exclusion if they have regular contact with significant others, have a sense of community, are not poor, are mobile, and are open to new experiences which enable them to grow on a personal level. The value of an additional trip is estimated at $A20.

Date of receipt of final manuscript: January 2010

1.0 Introduction

The concept of social exclusion has grown from work which sought to better understand and represent poverty. While poverty and social exclusion are related, social exclusion describes the existence of barriers which make it difficult or impossible for people to participate fully in society. While low income and unemployment are considered important barriers, other examples include poor health, limited education, ethnic minority status, age, and poor mobility.

The UK government's Social Exclusion Unit (SEU) undertook pioneering research around particular forms of social exclusion, transport being an early focus (Social Exclusion Unit, 2003). Links were drawn, for example, between the exclusion of people who do not have access to a car, and their needs for education, employment, access to health and other services and to food shops, as well as to sporting, leisure, and cultural activities. The ability to access such resources assists a person to be included in society and improve their well-being.

The work of the SEU has been significant in raising concerns about links between mobility, accessibility, and the prospects of a person being socially excluded.[1] While not specifically measuring social exclusion, related work was undertaken by the European Mobilate project, which examined the role of mobility in the well-being of older Europeans (Mollenkopf *et al.*, 2005). Social exclusion is viewed in that research as a factor which diminishes well-being. The Mobilate research showed a strong positive relationship between an older person's level of outdoor mobility and their quality of life. Research has also recently been reported for non-working elderly Canadians, again identifying significant association between transport mobility benefits and quality of life (Spinney *et al.*, 2009). Neither of these studies, however, puts monetary values on improvements in mobility (trip-making).

Until recently, there has been little application of social exclusion concepts within the transport field in Australia. However, groups who might be described as 'transport disadvantaged', in the sense that they have poor mobility, have been studied and these groups may overlap with those thought likely to be at risk of social exclusion, from mobility origins. For example, Alsnith and Hensher (2003), Harris (2005), and Golob and Hensher (2007) have researched transport issues for seniors, and Currie *et al.* (2005) have worked on accessibility to transport for youth in rural and regional Australia. By implication, measures to reduce

[1]Mobility relates to ease of movement and accessibility is ease of reaching destinations, the latter requiring attention to urban form, land use, and to the quality of destinations.

transport disadvantage are thought likely to improve the prospects for social inclusion, although such links have not been empirically validated.

Australian researchers, particularly concerned about the consequences of poor public transport service levels in the outer suburbs of Australian cities, have undertaken similar investigations to the SEU, to assess the likelihood that improved public transport service levels might reduce the risks of social exclusion in these areas. This research led to the adoption, by the Victorian State Government, of minimum bus service levels in outer urban Melbourne, described as 'social transit'. The implementation of these minimum service levels has led to very strong patronage growth and social benefits (Bell *et al.*, 2006; Loader and Stanley, 2009).

In building the argument for why new or substantially improved public transport services were needed in outer urban Melbourne, the initial absence of solid quantitative evidence about the value of such services to users was notable. This comment applies with particular force when there is a likelihood that a number of such users are at risk of social exclusion. While the traditional valuation approach of measuring consumers' surplus (or compensating variation) is appropriate for small changes in service levels, where some evidence of demand responsiveness often exists, new or dramatically improved public transport services invariably lack such behavioural evidence of values.

The absence of evidence about such valuations is not confined to Melbourne, but reflects a universal problem in assessing new or substantially improved public transport service levels. Thus, while it may be possible to mount a qualitative argument, on social equity or social justice grounds, about the importance of mobility in providing people with the opportunity to engage in activities that may increase their prospects of being socially included, valuation is another matter. The paper reports findings related to linkages between mobility and the risk of social exclusion, with particular emphasis on deriving a measure of willingness to pay for additional trips, consistent with the valuation principles that underlie most cost–benefit studies.

The risk that a person will be socially excluded is defined herein as the number of exclusion thresholds a person fails (that is, the more thresholds failed, the greater the risk of being socially excluded). This is explained further, below. This variable is a discrete representation of an underlying continuous scale and, as such, should be treated as an ordered response scale. A growing number of empirical studies involves the assessment of influences on a choice among ordered discrete alternatives. Ordered logit and probit models are well known, including extensions to accommodate random parameters and heteroscedasticity in unobserved variance (Bhat and Pulugurtha, 1998; Ferrer-i-Carbonell and Frijters, 2004; Greene, 2007).

The ordered choice model can also accommodate non-linear effects of any variable on the probabilities associated with each ordered level (see, for example, Eluru *et al.*, 2008). However, the traditional ordered choice model holds the threshold values fixed. This can lead to inconsistent (that is, incorrect) estimates of the effects of variables and, by implication, to incorrect estimates of implied relative values which may be derived from the models. Specifying the ordered choice model to account for threshold random heterogeneity, as well as underlying systematic sources of explanation for unobserved heterogeneity, is a logical extension in line with the growing interest in choice analysis in establishing additional candidate sources of observed and unobserved taste heterogeneity. The approach implemented herein generalises the existing approaches to ordered choice analysis with a polychotomous (in contrast to binary) ordered response scale.[2]

The paper is organised as follows. The next section discusses factors which relate to a person's likelihood of being at risk of social exclusion, together with ways of measuring relevant concepts. This is followed by the econometric specification of the generalised ordered choice model, focusing on the random threshold structure and its behavioural appeal. We then introduce the empirical context used to test this model. The empirical analysis that follows presents the estimated model, together with the associated marginal effects that are the basis of behavioural assessment. The willingness to pay for additional trips implied by the modelling is presented and compared with values derived from an alternative approach. The paper concludes with some observations on the merits of the extended model form.

2.0 Social Exclusion

2.1 Dimensions and mitigating factors

The concept of social exclusion is often used rather loosely and has, therefore, been difficult to measure. However, ideas about what social exclusion comprised appeared to show consistent trends from about 2000, with work from a key group of researchers in the UK (see, for example, Gordon *et al.*, 2000; Levitas, 2000; Burchardt *et al.*, 2002). Income and employment status were included in all models, and most included variables of social relations, participation, civic engagement and support in times of need. The measurement approach used in the current

[2]The model developed by Ferrer-i-Carbonell and Frijters (2004) introduces random thresholds but is limited to binary choice.

project drew on the four dimensions of social exclusion identified by the London School of Economics approach (Burchardt *et al.*, 2002), but with an additional dimension of participation, as commonly used by others.[3]

The current project used five dimensions to indicate a person's risk of being socially excluded (defined as SOCEXA in this study):

- household income — less than a threshold of $500 gross per week;
- employment status — neither employed, retired, in education or training, looking after family, nor undertaking voluntary work;
- political activity — did not contribute to/participate in a government political party, campaign, or action group to improve social/environmental conditions, to a local community committee/group in the past 12 months;
- social support — not able to get help if you need it from close or extended family, friends or neighbours;
- participation — did not attend a library, sport (participant or spectator), hobby, or arts event in the past month.

This study assumed that the more of these dimension thresholds that describe a person's situation (which we call failing the threshold), the greater is their risk of social exclusion. This approach weighs each dimension equally.

The dependent variable, SOCEXA, is a categorical variable with six possible values, being the number of exclusion hurdles that a person fails (from zero to five inclusive). This was subsequently reduced to four categories in the empirical analysis, because no survey respondent failed against all five hurdles and only one failed against four. The ordered response values for SOCEXA thus ranged from zero to three.

A review of the broad literature in economics, psychology, social work, and transport suggests that a number of key factors may be at play in mitigating the risk of social exclusion. These include age, household income, a suite of personality and well-being variables, indicators of a person's social capital, a person's attachment to community, perception of personal safety, and a person's travel activity (measured separately as the number of trips on a day and the number of kilometres travelled, as a statement on current accessibility and activity engagement). The study data collection process gathered information relevant to all these variables, with some key data summarised in Tables 1 and 2.

[3]The LSE used a dimension termed 'social interaction' but describe this as social support: a lack of someone who could offer support in one of five dimensions — listen, comfort, help in crisis, relax with, really appreciates you. The current study included the dimension of 'social support' and added 'participation', referring to involvement in community-provided services or events.

2.2 Social Capital and Connection With Community

A person is considered less likely to be at risk of social exclusion when they are embedded in societal structures: family and friends, the community and society (Bronfenbrenner, 1979). Two key concepts, social capital and connection with community, have become an increasingly important part of the international social policy debate in recent years, particularly in the United States and Australia. Very little evidence is available on the association between social capital, connections with community, social exclusion, and the ability to be mobile (Currie and Stanley, 2008). Putnam (2000) has suggested that there are negative links between car dependence and the development of effective social capital. Urry (undated) argues that to be a full, active, and engaged member of society requires social capital within localities and participation involves transportation and mobility.

As with social exclusion, there is definitional variability around social capital and community connectedness. For this study, social capital is defined as a person's social networks plus associated issues of trust and reciprocity (Stone *et al.*, 2003). Each of these components was measured independently. Community connections occur when people become actively engaged in the community. They feel socially connected, may become volunteers or leaders, and a sense of community pride is established (Vinson, 2004).

Social capital was measured in this study by: (a) measures of the frequency with which respondents keep in touch with members of their close family, members of their extended family, friends/intimates, neighbours, work colleagues, people associated with groups in their community (such as church, sporting, clubs, school self-help, or voluntary groups) and government officials/community leaders; (b) measures of the extent to which respondents trust people in general; and (c) measures of reciprocity (the extent to which respondents feel that people are willing to help out in their local community). Relevant aggregate responses are shown in Tables 1 and 2.

A comprehensive measurement of community engagement involves a wide range of possible measures (Currie and Stanley, 2008). For the current study, the answer to the question, 'I think my neighbourhood is a good place for me to live', was used as a measure of community connectedness. Answers were measured on a seven-point Likert scale, from 'strongly disagree' to 'strongly agree' and, for modelling purposes, responses were treated as reflecting a continuous variable.[4]

[4]This is in line with the approach taken to the comprehensive Sense of Community Index by authors such as Long and Perkins (2003) and Obst and White (2004). In future work on the dataset, the authors will broaden their analysis of community connections.

In modelling, the various measures of social capital were all treated as dummy variables, because they are rated for various groups of people (for example, close family, extended family, close friends) on a broad frequency of interaction basis (not at all; sometimes; frequently), rather than on a continuous scale.

2.3 Psychological aspects

There is likely to be an association between social exclusion and personal attributes (Mollenkopf *et al.*, 2005). The current study utilised measures which assess both subjective and psychological aspects of well-being, and cognitive (Psychological Well-being) and affective (Positive Affect and Negative Affect) components. Furthermore, personality measures were included to (1) enable the unique contributions of other variables to be better assessed and (2) to determine any interaction effects of personality, especially with regard to extraversion and locus of control.

2.3.1 Subjective well-being

Two measures of subjective well-being were used. The Positive and Negative Affect Schedule (Watson *et al.*, 1988) (PANAS) was employed to assess positive and negative emotions, both being needed because they are believed to be independent constructs and may contribute to social exclusion differently (Diener and Emmons, 1984; Ruini *et al.*, 2003). The scale comprises ten positive emotional descriptors such as ‘inspired’ and ‘excited’ and ten negative emotional descriptors such as ‘guilty’ and ‘upset’. Respondents indicated the extent to which they generally felt this way on a 5-point Likert scale, ranging from 1 = ‘very slightly or not at all’ to 5 = ‘extremely’.

A domain-specific measure is the Personal Well-being Index (PWI) (International Wellbeing Group, 2006). It contains eight items assessing one’s level of satisfaction with seven theoretically derived quality-of-life domains: standard of living, health, achieving in life, relationships, safety, community-connectedness and future security, as well as one global question asking ‘How satisfied are you with your life as a whole?’ Responses are made on a ten-point scale ranging from ‘completely dissatisfied’ to ‘completely satisfied’.[5] The seven domain scores can be summed to derive a total subjective well-being score or each item can be analysed as a separate variable.

[5]The PWI has been shown to have satisfactory psychometric properties as detailed in reports on the Australian Unity Wellbeing Index (http://www.deakin.edu.au/research/acqol/index_wellbeing/index.htm).

2.3.2 Psychological well-being

Subjective well-being is based on maximising pleasure and minimising pain. Psychological well-being accentuates the importance of life meaning and personal growth for sustained well-being. It espouses that factors such as life purpose, opportunities for growth and reaching one's potential, and having positive relationships are important for well-being.

Ryff's (1989) scales of psychological well-being are aligned with this latter perspective. The scale assesses six theoretically derived dimensions of psychological well-being: self-acceptance, autonomy, environmental mastery, positive relations with others, personal growth, and purpose in life. The forty-two-item version of the measure was employed for the current study, as this was thought to provide a good balance between the need for brevity and satisfactory psychometric qualities. Responses are made on a Likert scale ranging from 'strongly disagree' to 'strongly agree'.

2.3.3 Personality

One of the strongest and most consistent individual difference factors associated with well-being is personality and most especially, the personality trait of extraversion (Diener *et al*., 1999). One explanation for this is that extraverts are happier because of their heightened level of social involvement relative to introverts (Argyle and Lu, 1990). Hence, when examining the relationship between well-being and social exclusion, it is important to seek to identify the contributions made by personality factors such as extraversion to ascertain the unique contributions of additional factors.

The Ten Item Personality Inventory (TIPI) (Gosling *et al*., 2003) was used in the current study, a ten-item self-report measure of the Big-five personality dimensions: openness, conscientiousness, extraversion, agreeableness, and neuroticism (emotional stability). It is intended for use where personality is not a major focus of the study and in time-limited circumstances. Responses are on a seven-point Likert scale ranging from 'disagree strongly' to 'agree strongly'. Higher scores reflect higher levels of the relevant personality dimension. Initial reviews of the study data suggested that 'extraversion' was the most likely measure from this set to be an important contributor to explaining a person's risk of social exclusion.

2.3.4 Locus of control

Locus of control, according to Rotter (1966), concerns generalised internal or external beliefs about future events and outcomes. Internal control refers to the belief that control of future outcomes is due to personal attributes and behaviours, while external control refers to the expectancy that control resides in the hands of others or as a result of chance. It has been found that external locus of control is associated with negative affect (Emmons and Diener, 1985) and internal locus of control is a strong predictor of life satisfaction (Hong and Giannakopoulos, 1994). Rotter's (1966) twenty-nine forced choice item scale was used to measure locus of control. Low scores reflect an internal orientation.

2.4 Perceptions of safety

It was thought likely that if people do not feel safe in various contexts, this could impact on their risk of being socially excluded. This is consistent with the findings of a number of research projects (Social Exclusion Unit, 2003). Three contexts were included in this regard: feeling safe on and around public transport; feeling safe in the respondent's own street at night; feeling safe in the respondent's home at night. Five possible responses ranged from 'very unsafe' through to 'very safe'. None of these variables proved to be significant in the subsequent analysis, so they are not considered further in this paper.

3.0 An Ordered Polychotomous Choice Model with Preference Heterogeneity in the Thresholds

The ordered response model is well established for the analysis of categorical, non-quantitative responses (see Greene and Hensher, 2010). The model foundation is an underlying random utility (or latent regression) model,

$$y_i^* = \boldsymbol{\beta}'\mathbf{x}_i + \varepsilon_i, \tag{1}$$

in which the continuous latent utility, y_i^* is observed in discrete form through a censoring mechanism (equation (2)):

$$\begin{aligned} y_i &= 0 \text{ if } \quad \mu_{-1} < y_i^* \leqslant \mu_0, \\ &= 1 \text{ if } \quad \mu_0 < y_i^* \leqslant \mu_1, \\ &= 2 \text{ if } \quad \mu_1 < y_i^* \leqslant \mu_2, \\ &= \ldots \\ &= J \text{ if } \quad \mu_{J-1} < y_i^* \leqslant \mu_J. \end{aligned} \tag{2}$$

The model contains the unknown marginal utilities, $\boldsymbol{\beta}$, as well as $J+2$ unknown threshold parameters, μ_j, all to be estimated using a sample of

n observations, indexed by $i = 1, \ldots, n$. The data consist of the covariates, $\mathbf{x}_i$ and the observed discrete outcome, $y_i = 0,1, \ldots, J$, such as a Likert scale response or an ordered index. The conventional assumptions for the error disturbance are that ε_i is continuous with conventional cdf, $F(\varepsilon_i \mid \mathbf{x}_i) = F(\varepsilon_i)$ with support equal to the real line, and with density $f(\varepsilon_i) = F'(\varepsilon_i)$. The assumption of the distribution of ε_i includes independence from $\mathbf{x}_i$. The probabilities associated with the observed outcomes are given as equation (3):

$$\text{Prob}[y_i = j \mid \mathbf{x}_i] = \text{Prob}[\varepsilon_i \leqslant \mu_j - \boldsymbol{\beta}'\mathbf{x}_i] - \text{Prob}[\mu_{j-1} - \boldsymbol{\beta}'\mathbf{x}_i],$$
$$j = 0, 1, \ldots, J. \tag{3}$$

Several normalisations are needed to identify the model parameters:

(i) given the continuity assumption, in order to preserve the positive signs of the probabilities, we require $\mu_j > \mu_{j-1}$;
(ii) if the support is to be the entire real line, then $\mu_{-1} = -\infty$ and $\mu_J = +\infty$;
(iii) assuming that $\mathbf{x}_i$ contains a constant term, we will require $\mu_0 = 0$.[6] Given the overall constant, $J - 1$ threshold parameters are needed to partition the real line into the $J + 1$ distinct intervals.

We impose the identifying restriction $\sigma_\varepsilon =$ a known constant, $\bar{\sigma}$, and assume that $\text{Var}[\varepsilon_i \mid \mathbf{x}_i] = \pi^2/3$ in the logit model form implemented below. The likelihood function for estimation of the model parameters is based on the implied probabilities given in equation (4):

$$\text{Prob}[y_i = j \mid \mathbf{x}_i] = F(\mu_j - \boldsymbol{\beta}'\mathbf{x}_i) - F(\mu_{j-1} - \boldsymbol{\beta}'\mathbf{x}_i) > 0, \quad j = 0, 1, \ldots, J. \tag{4}$$

Estimation of the parameters is a straightforward problem in maximum likelihood estimation (see, for example, Greene, 2008). Based on Greene and Hensher (2010), we present an extension of the basic model (4) above to allow for three ways in which individual preference heterogeneity can substantively appear: in the random utility model (the marginal utilities), in the threshold parameters, and in the scaling (variance) of the random components. The intrinsic heterogeneity in utility functions across individuals is captured by writing

$$\boldsymbol{\beta}_i = \boldsymbol{\beta} + \boldsymbol{\Delta}\mathbf{z}_i + \boldsymbol{\Gamma}\mathbf{v}_i, \tag{5}$$

where $\boldsymbol{\Gamma}$ is a lower triangular matrix and $\mathbf{v}_i \sim N\,[\mathbf{0}, \mathbf{I}]$. $\boldsymbol{\beta}_i$ is normally distributed across individuals with conditional mean (equation (6)) and

[6]With a constant term present, if this normalisation is not imposed, then adding any non-zero constant to μ_0 and the same constant to the intercept term in $\boldsymbol{\beta}$ will leave the probability unchanged.

conditional variance (equation (7)):

$$E[\boldsymbol{\beta}_i \mid \mathbf{x}_i, \mathbf{z}_i] = \boldsymbol{\beta} + \boldsymbol{\Delta}\mathbf{z}_i, \tag{6}$$

$$\mathrm{Var}[\boldsymbol{\beta}_i \mid \mathbf{x}_i, \mathbf{z}_i] = \boldsymbol{\Gamma}\mathbf{I}\boldsymbol{\Gamma}' = \boldsymbol{\Omega}. \tag{7}$$

This is a generalised random parameters formulation including thresholds modelled randomly and non-linearly as equation (8).

$$\mu_{ij} = \mu_{i,j-1} + \exp(\alpha_j + \boldsymbol{\delta}'\mathbf{r}_i + \sigma_j w_{ij}), \quad w_{ij} \sim N[0,1]. \tag{8}$$

With normalisations and restrictions $\mu_{-1} = -\infty$, $\mu_0 = 0$, $\mu_J = +\infty$. For the remaining thresholds, we have equation (9) which preserves the ordering of the thresholds and incorporates the necessary normalisations, and allows observed variables and unobserved heterogeneity to play a role both in the utility function and in the thresholds. The thresholds, like the regression itself, are shifted by both observable ($\mathbf{r}_i$) and unobservable (w_{ij}) heterogeneity.

$$\begin{aligned}
\mu_1 &= \exp(\alpha_1 + \boldsymbol{\delta}'\mathbf{r}_i + \sigma_1 w_{j1}) \\
&= \exp(\boldsymbol{\delta}'\mathbf{r}_i)\exp(\alpha_1 + \sigma_1 w_{j1}) \\
\mu_2 &= \exp(\boldsymbol{\delta}'\mathbf{r}_i)\,[\exp(\alpha_1 + \sigma_1 w_{j1}) + \exp(\alpha_2 + \sigma_2 w_{j2})], \\
\mu_j &= \exp(\boldsymbol{\delta}'\mathbf{r}_i)\left(\sum_{m=1}^{j}\exp(\alpha_m + \sigma_m w_{im})\right), \quad j = 1, \ldots, J-1 \\
\mu_J &= +\infty.
\end{aligned} \tag{9}$$

The probabilities are all positive and sum to one by construction. If $\boldsymbol{\delta} = \mathbf{0}$ and $\sigma_j = 0$, then the original model is returned, with $\mu_1 = \exp(\alpha_1)$, $\mu_2 = \mu_1 + \exp(\alpha_2)$, and so on. The disturbance variance is allowed to be heteroscedastic, now specified randomly as well as deterministically. Thus,

$$\mathrm{Var}[\varepsilon_i \mid \mathbf{h}_i, e_i] = \sigma_i^2 = \exp(\boldsymbol{\gamma}'\mathbf{h}_i + \tau e_i)^2, \tag{10}$$

where $e_i \sim N[0,1]$. Let $\mathbf{v}_i = (v_{i1}, \ldots, v_{iK})'$ and $\mathbf{w}_i = (w_{i1}, \ldots, w_{i,J-1})'$. Combining terms, the conditional probability of outcome is given in equation (11) (see Greene and Hensher, 2010).

$$\begin{aligned}
&\mathrm{Prob}[y_i = j \mid \mathbf{x}_i, \mathbf{z}_i, \mathbf{h}_i, \mathbf{r}_i, \mathbf{v}_i, \mathbf{w}_i, e_i] \\
&\quad = F\left[\frac{\mu_{ij} - \boldsymbol{\beta}_i'\mathbf{x}_i}{\exp(\boldsymbol{\gamma}'\mathbf{h}_i + \tau e_i)}\right] - F\left[\frac{\mu_{i,j-1} - \boldsymbol{\beta}_i'\mathbf{x}_i}{\exp(\boldsymbol{\gamma}'\mathbf{h}_i + \tau e_i)}\right].
\end{aligned} \tag{11}$$

The term that enters the log likelihood function is unconditioned on the unobservables. Thus,

$$\text{Prob}[y_i = j \mid \mathbf{x}_i, \mathbf{z}_i, \mathbf{h}_i, \mathbf{r}_i] = \int_{\mathbf{v}_i, \mathbf{w}_i, e_i} \left(F\left[\frac{\mu_{ij} - \boldsymbol{\beta}_i' \mathbf{x}_i}{\exp(\boldsymbol{\gamma}' \mathbf{h}_i + \tau e_i)}\right] - F\left[\frac{\mu_{i,j-1} - \boldsymbol{\beta}_i' \mathbf{x}_i}{\exp(\boldsymbol{\gamma}' \mathbf{h}_i + \tau e_i)}\right]\right) f(\mathbf{v}_i, \mathbf{w}_i, e_i) d\mathbf{v}_i d\mathbf{w}_i de_i. \quad (12)$$

The model is estimated by maximum simulated likelihood (Greene and Hensher, 2010). All elements of the generalised form are investigated in the empirical study, although as shown in the final model, not all elements were found to be statistically significant.

4.0 Empirical Application: Assessment of Social Exclusion

The study conducted face-to-face interviews across Melbourne with 443 adults (Currie and Delbosc, 2009).[7] The survey sampling frame was designed to ensure coverage of inner and outer metropolitan areas, people living in areas within walking distance to public transport and outside such distance, low and high income levels, and a representative age distribution.[8] It was designed as a follow-on survey from an existing Melbourne household travel survey, to extend data scope without extending the time for administering the survey. Because of the follow-on nature of this survey, a random sample of interviewees who had completed the travel survey was invited to opt-in to the present survey.

Highly disadvantaged people were under-represented in the survey, having been similarly under-represented in the prior household travel survey, a common problem for surveys. A separate study has been undertaken with a sample of such people, working through welfare agencies (not reported in the present paper). This factor aside, the sample was regarded as representative of the various strata that were required.

The survey was administered by the same professional survey organisation that administered the travel survey. The survey questionnaire included five sections.

- screening questions (for example, household size, motor vehicles, income, children aged under 18, Aboriginality, disability);

[7]People aged 15–17 are the subject of separate research.
[8]The general study approach and sample frame development are discussed in Currie and Delbosc (2009).

Table 1
Broad Survey Data

Variable (Model variable)	*Adults only sample (N = 443)*
Age	
18–35	11%
36–50	29%
51–65	30%
>65	30%
Average respondent age	55 years
Household income	
Under $A500 per week	28%
$A501–1099 pw	36%
$A1100–2000 pw	20%
>$A2000 pw	17%
Average daily household income (HINCPDY)	$A190.21 (std. dev. $188.22)
Average trips per day (Numtrps)	3.6 (std. dev. 2.8)
Average kilometres per day (kms)	36.6 (std. dev. 57.5)
Number of social exclusion thresholds failed (SOCEXA)	
0 thresholds	41%
1 threshold	37%
2 thresholds	14%
3 or more thresholds	7%
Social capital/community strength measures	
How much do you trust people in your local community (trust)?	Not at all = 3%, sometimes = 68%, Yes definitely = 28%
How willing are people to help out in your local community (reciprocity)?	Not at all = 3%, sometimes = 60%, frequently 37%
I think my neighbourhood is a good place for me to live (Socomm)	Strongly agree = 30%, agree = 56%, slightly agree = 9%, neither agree nor disagree = 2%, slightly disagree = 2%, disagree = 1%, strongly disagree = 0%
Well-being measures	
Personal Well-being Index	Mean: 7.4 SD: 1.37 range: 1.12 to 10
Positive Affect	Mean: 3.6 SD: 0.59 range: 1.5 to 5
Negative Affect	Mean: 1.6 SD: 0.52 range: 1.0 to 4.3
Psychological well-being (autonomy)	Mean: 4.6 SD: 0.64 range: 2.9 to 6.0
Psychological well-being (environmental mastery)	Mean: 4.6 SD: 0.65 range: 1.9 to 6.0
Psychological well-being (personal growth)	Mean: 4.7 SD: 0.67 range: 1.9 to 6.0
Psychological well-being (positive relations with others)	Mean: 4.8 SD: 0.60 range: 2.7 to 6.0
Psychological well-being (purpose)	Mean: 4.5 SD: 0.69 range: 2.0 to 6.0
Psychological well-being (self-acceptance)	Mean: 4.5 SD: 0.68 range: 1.7 to 6.0
Personality	
Extraversion	Mean: 4.3 SD: 1.4 range: 1 to 7
Locus of control	Mean: 10.2 SD: 10.2 range: 1 to 22

Table 2
Social Networks: How Often Do You Keep in Touch with the Following People?

Group	n.a. (%)	Never (%)	Less than once a year (%)	More than once a year (%)	About once a month (%)	About once a week (%)	Most days (%)
Members of your close family	0	1	1	3	12	39	44
Members of your extended family	2	5	6	1	34	29	8
Friends/intimates	0	1	1	4	24	45	25
Neighbours	0	3	8	8	24	35	24

- Section A: social exclusion (various social exclusion indicator questions and questions related to social capital, community strength and social well being measures);
- Section B: well-being (various well-being and personality measures);
- Section C: transport (building on details in the prior household travel survey);
- close (education, country of birth, various income questions, including relative poverty).

An overview of key data items is given in Tables 1 and 2.

Table 1 shows that the average daily trip rate among sample respondents was 3.6. However, the rate for people who failed against none of the thresholds for social exclusion risk was 3.8 (not shown in Table 1). This fell to 3.2 for people who failed against one or more thresholds, falling further to 2.8 trips per day for people who failed two or more thresholds. In short, people assessed as being at a relatively greater risk of social exclusion are travelling less frequently than others.

Generally, the descriptive data for the well-being and personality measures conform with means and standard deviations found in other well-being studies. Most noteworthy is the mean for the PWI which is within the range typically obtained for Western populations, namely ±5 per cent of the 70 per cent value of the measurement scale (Cummins, 2001). This suggests that, in terms of well-being, the current sample is a good representation of the standard of well-being typically found in the general community.

Table 2 shows that most people had contact with members of their close family at least weekly. Contact with extended family members was less frequent, weekly to monthly contact being most common. Contact with friends/intimates and with neighbours was less frequent than with members of the close family but more frequent than with members of the extended family. A small number of people never or rarely had social contact with family or friends. They risk missing the social support and potential opportunities that may come from these networks.

5.0 Empirical Analysis: Social Exclusion Model

5.1 Model results

The final model is given in Table 3. This model was selected after extensive assessment of the full range of candidate variables in the survey. The generalised ordered logit model has an overall log-likelihood at convergence of −441.935, compared to the log-likelihood with no information on the explanatory variables and constant of −531.71.

This model has two particularly important features: first, the non-linear specification of household income enables derivation of the marginal willingness to pay for daily trip rates as a function of household income. In line with previous studies on happiness and social well-being, we investigated various functional forms for household income and found that the quadratic had the best statistical fit in terms of the *t*-value, while also supporting the hypothesis that the marginal utility of household income declines as income increases.

Second, we have strong evidence that the threshold parameters exhibit individual-specific heterogeneity, that is due to four observed person-specific effects: personal well-being index (PWI), kilometres travelled (kms), Negative Affect (NA) and Age (age). The mean estimates of the threshold distributions are statistically significant; however, the presence of observed sources of heterogeneity has not resulted in unobserved heterogeneity in the thresholds being statistically significant. In particular, three of the four observed threshold covariates are positive and one (age) is negative. This suggests that individuals with higher values for the PWI, NA, and daily kms tend to have lower threshold parameter estimates within each threshold parameter distribution (given that the mean is negative) than individuals with lower values, and the reverse applies for age. What this implies, for example, is that as one ages, all other influences remaining unchanged, the probability of reducing the number of hurdles associated with social exclusion is higher. By not accounting for these observed sources of heterogeneity, we would be forcing all individuals to display the same threshold parameter values, which would result in a different distribution of probability outcomes associated with each level of social exclusion.

Table 3 shows that several variables are significantly associated with the risk of being socially excluded. Socomm is a measure of a person's

Table 3
Generalised Ordered Logit Model (t-ratios in brackets), 443 Observations Dependent variable is SOCEXA

Attribute	Units	Generalised ordered logit	Mean
Constant		4.1592 (7.03)	
Person's sense of community (Socomm)	1–7 scale	−0.3874 (−4.9)	5.008
Contact with members of the close family more than once a year (Scnmgt1a)	1.0	1.3127 (2.85)	0.0248
Never have contact with members of extended family (Scnenev)	1.0	0.8984 (3.63)	0.0519
Do not trust people in general (Scntnot)	1.0	0.8912 (3.32)	0.0339
Household gross income per day squared	$(\$/day)^2$	−0.00000769 (−7.74)	55,265
Number of trips on travel day (Numtrps)	Trips/day	−0.05907 (−2.65)	3.623
Personal growth (Pwbperg)	1–6 scale	−0.2944 (−3.22)	4.7156
Threshold parameters: ($u_1 = 0$)			
μ_2		−1.2063 (−4.47)	
μ_3		−1.3004 (−6.34)	
Standard deviation of threshold parameters			
μ_2		0.10259 (0.12)	
μ_3		0.21866 (0.28)	
Systematic influences on random thresholds			
Personal well-being index (PWI)	1–10 scale	0.12735 (19.24)	7.409
Daily kilometres of travel (kms)	Kilometres per day	0.00208 (7.0)	36.56
Negative affect (NA)	1–5 scale	0.27674 (17.49)	1.637
Age of individual	Years	−0.00049 (−2.77)	55.28
Count of choice responses			
0		183	
1		165	
2		63	
3		31	
Log-likelihood at zero		−531.71	
Log-likelihood at convergence		−441.935	

connection with community. Given the negative sign on this variable, the more someone agrees with the statement, 'I think my neighbourhood is a good place for me to live', the less likely they are to be at risk of social exclusion.

The first two statistically significant social capital variables are both measures of the frequency with which a person has contact with various important others. Contact with a person's close family (Scnmgt1a) and with their extended family (Scnenev) were both significant. Both these dummy variables effectively appear as limits on interactions to foster inclusion. Contact with close friends, people in the local community, and people in general were tested and not found to be significant.

The third significant social capital measure is a measure of trust. The rated measure (Scntnot) is a dummy variable for 'people in general'. The positive co-efficient on Scntnot says that the risk of social exclusion is greater if the person does not trust people in general.

Personal Growth (variable Pwbperg) also stands out as significantly linked to risk of social exclusion. People generally reporting low levels of Personal Growth tend to experience a sense of personal stagnation and can become generally disconnected with social life. Conversely, individuals who are high on Personal Growth do not feel obstructed by life circumstances. Instead, they are open to trying new experiences and subsequently feel that they are constantly developing and realising their full potential. It is not surprising, therefore, that social exclusion and Personal Growth are inversely related, such that those highest on Personal Growth are judged to be least likely to be at risk of social exclusion.

Household income and number of trips per day are both significant influences on the risk of being socially excluded. The higher a respondent's household income and the more trips are made per day, the less the risk of being socially excluded.

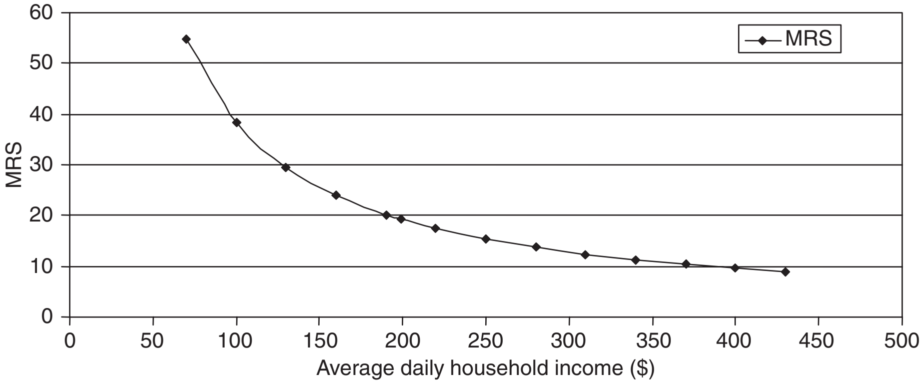
Overall, the model suggests that the risk of someone being socially excluded is reduced, the higher their connection with community, household income, realised mobility, and level of personal growth. The risk of social exclusion increases if they only have contact with members of their close family more than once a year (but less than monthly), never have contact with members of their extended family, and do not trust people in general.

Finally, the threshold parameters on the utility scale (that is, μ_1 and μ_2) suggest that the switching values for utility are, at the mean, statistically significant, but there is no evidence of randomly distributed unobserved heterogeneity. However, there is heterogeneity associated with systematic sources, namely the personal well-being index and daily kilometres of travel. Hence, all other influences remaining unchanged, the threshold utility points are less negative for individuals undertaking more kilometres per day and with a more positive personal well-being index. Another way of stating this is that individuals who get out and about more (as proxied by daily kilometres) and who have greater personal well-being, tend to have fewer social exclusion thresholds to cross.

5.2 Valuation of additional trips

A key focus of this paper is willingness to pay for increased mobility, as measured by trip activity. The data in Table 3 can be used to derive the

Figure 1
Marginal Rate of Substitution Between Number of Daily Trips and Average Daily Household Income



value of an additional trip at any given household income level, through estimation of the Marginal Rate of Substitution (MRS) between trips and income (for a common time period, such as a day). Figure 1 summarises the resulting MRS between trip rates and gross household income, reflecting willingness to pay for an additional trip. We find that the mean level of daily equivalent household income that a representative individual is willing to pay is up to \$A19.30 for an additional trip. This value is not mode-specific. It is essentially willingness to pay to engage in an additional activity, since the study's trip diaries align trips and activities.

This mean estimate declines as household income increases, the implied value approximately halving as income doubles. This is broadly in line with the UK Treasury Green Book (2003, Annex 05), which deals with distributional weighting in project evaluation. That approach notes empirical evidence suggesting that, as income is doubled, the marginal value of consumption to individuals is about halved. This is approximately true for trips in Figure 1. The Green Book approach implies that, in a cost–benefit framework, benefits to a person on half-average income levels would be weighted at twice that of the average income earner. The values of an additional trip derived from the choice modelling presented in this paper closely align with this weighting.

Why might values be higher at lower income levels? Our interpretation is that, in our sample, people on lower incomes take fewer trips. If we can add a trip, this is a large relative increase in mobility and associated activity levels and a relatively high willingness to pay is not surprising, compared to the marginal trip value to someone who undertakes more trips (and has higher income). For someone with low income, if that additional trip is associated with new employment, then the marginal value could be very high indeed.

How does this value of \$A19.30 for an additional trip compare to values that might be derived from the application of generalised travel cost approaches to benefit measurement? Generalised travel cost is usually measured as a combination of financial costs (vehicle operating costs or fares) plus a valuation of the elements of travel time savings. The latter includes weighting of attributes of journeys (walk, wait, and so on) according to user perceptions factored by a value of travel time savings.

The conventional generalised cost approach applied within the context of the Melbourne metropolitan area is documented in local and national guidelines for the appraisal of transport projects (Department of Infrastructure, 2005; Australian Transport Council, 2006). Applying that approach, based on parameters that are comparable to the transport survey results used in this paper, results in an implied value of \$A7.07 for an additional car trip and \$A9.56 for a public transport journey. However, the marginal value of additional trips, which is the focus of this paper, is typically estimated in transport project appraisals using the consumers' surplus 'rule of a half' applied to 'generated traffic'. Under this approach the implied value of additional trips is about \$A3.50 for a car trip or \$A4.80 for a public transport trip.

This is well below the representative estimate of \$A19.30 derived in this paper. The difference is likely to be due to generalised cost estimates being appropriate for benefit estimation for small changes in travel opportunities (such as a slightly faster trip) but not for major changes in trip behaviour (for example, a much higher public transport service frequency or a new service). With a typical daily trip rate of about 2.5 to 5 return trips, an additional trip is a non-marginal change in activity, where valuation should incorporate expected consumer's surplus on the travel activity, not be simply estimated based on expected travel costs. This implies higher values for non-marginal changes in travel activity, which is what the result modelled in this paper indicates.

5.3 Partial effects of each influencing source

A direct interpretation of the magnitude and sign of the parameter estimates in Table 3 is strictly not informative, given the logit transformation of the choice-dependent variable. Interpretation of the coefficients in the ordered choice model is more complicated than in the ordinary regression setting. There is no natural conditional mean function in the model. The outcome variable, y, is merely a label for the ordered, non-quantitative outcomes. As such, there is no conditional mean function, $E[y|\mathbf{x}]$ to analyse. In order to interpret the parameters, one typically refers to the probabilities themselves. A partial (or marginal) effect is the influence a one-unit change in an explanatory variable has on the probability of selecting a particular outcome, *ceteris paribus*.[9] The marginal effects need not have the same sign as the model parameters.

The generalised ordered choice model contains four points at which changes in the observed variables can induce changes in the probabilities of the outcomes, in the thresholds, μ_{ij}, in the marginal utilities, $\boldsymbol{\beta}_i$, in the utility function, $\mathbf{x}_i$ and in the variance, σ_i^2. For convenience, let a vector $\mathbf{a}_i$ denote the union of $(\mathbf{x}_i, \mathbf{r}_i, \mathbf{z}_i, \mathbf{h}_i)$. This allows for cases in which variables appear at more than one place in the model. $\mathbf{h}_i$ is the only element that was not statistically significant in the model in Table 2 and will be excluded from now on. The partial effect of a change in an element of $\mathbf{a}_i$ on the probability will depend on where it appears in the specification. For cases in which a variable appears in more than one location, the partial effect will be the sum of the two or three terms. To avoid a cumbersome re-parameterisation of the model, we assume at this point that $\mathbf{a}_i$ appears in full throughout the model; that is, as if $\mathbf{a}_i = \mathbf{x}_i = \mathbf{r}_i = \mathbf{z}_i$. Thus, we write the probability of interest as equation (13).

$$\begin{aligned}\text{Prob}(y_i = j \mid \mathbf{a}_i) &= \int_{\mathbf{v}_i, \mathbf{w}_i, e_i} \left(F\left[\frac{\mu_{ij} - (\boldsymbol{\beta} + \boldsymbol{\Delta}\mathbf{a}_i + \boldsymbol{\Gamma}\mathbf{v}_i)'\mathbf{a}_i}{\exp(\tau e_i)}\right] \right. \\ &\quad \left. - F\left[\frac{\mu_{i,j-1} - (\boldsymbol{\beta} + \boldsymbol{\Delta}\mathbf{a}_i + \boldsymbol{\Gamma}\mathbf{v}_i)'\mathbf{a}_i}{\exp(\tau e_i)}\right]\right) f(\mathbf{v}_i, \mathbf{w}_i, e_i)\, d\mathbf{v}_i d\mathbf{w}_i de_i. \qquad (13)\end{aligned}$$

μ_{ij} is defined in equation (9). Then, the set of partial effects is given as equation (14).

$$\begin{aligned}\frac{\partial\,\text{Prob}(y_i = j \mid \mathbf{a}_i)}{\partial \mathbf{a}_i} &= \int_{\mathbf{v}_i, \mathbf{w}_i, e_i} \left(f\left[\frac{\mu_{ij} - \boldsymbol{\beta}_i'\mathbf{a}_i}{\exp(\tau e_i)}\right] \frac{1}{\exp(\tau e_i)} (-\boldsymbol{\beta}_i - 2\boldsymbol{\Delta}\mathbf{a}_i + \mu_{ij}\boldsymbol{\delta}) \right) f(\mathbf{v}_i, \mathbf{w}_i, e_i)\, d\mathbf{v}_i d\mathbf{w}_i de_i \\ &\quad - \int_{\mathbf{v}_i, \mathbf{w}_i, e_i} \left(f\left[\frac{\mu_{i,j-1} - \boldsymbol{\beta}_i'\mathbf{a}_i}{\exp(\tau e_i)}\right] \frac{1}{\exp(\tau e_i)} (-\boldsymbol{\beta}_i - 2\boldsymbol{\Delta}\mathbf{a}_i + \mu_{i,j-1}\boldsymbol{\delta}) \right) f(\mathbf{v}_i, \mathbf{w}_i, e_i)\, d\mathbf{v}_i d\mathbf{w}_i de_i. \qquad (14)\end{aligned}$$

[9]This holds for continuous variables only. For dummy (1,0) variables, the marginal effects are the derivatives of the probabilities given a change in the level of the dummy variable.

The sum of three terms in the middle of the expressions shows the three parts of a compound partial effect; in turn, these are the components of the change (a) due directly to change in $\mathbf{x}_i$, (b) indirectly due to change in the variables that influence $\boldsymbol{\beta}_i$, and (c) due to changes in the threshold parameters, respectively. The partial effects must be computed by simulation. If a variable appears only in $\mathbf{x}_i$, then this formulation retains both the 'parallel regressions' and 'single crossing' features (see Greene and Hensher, in press, 2010, for more details). Nonetheless, the effects are highly nonlinear. However, if a variable appears anywhere else in the specification, then neither of these properties will remain.

Given that the marginal effects are derivatives, not probabilities, they are not bounded by zero and one and can be negative. If the explanatory variable is very small, its coefficient will be very large (hence, we do not report the estimates for household income squared since that is a very small number). We provide, in Table 4, the marginal (or partial) effects which do have substantive behavioural meaning, defined as the derivatives of the choice probabilities (equation (13)). As such they sum to zero across all four levels of the dependent variable. The four estimates in Table 4 for each variable are of greatest behavioural meaning within each variable, in contrast to between variables. For example, Socomm has a much higher and positive derivative for the level $Y = 0$, suggesting that the probability that the person has not failed against any of the five indicators of risk of

Table 4

Partial Effects (Y(SOCEXA) = 0, 1, 2, 3)

(Computed by averaging over observations during simulations)

Attribute	*Generalised ordered logit (equation (14))*
Direct partial effects	
Person's sense of community (Socomm)	0.1194, −0.0322, −0.0536, −0.0334
Contact with members of the close family more than once a year (Scnmgt1a)	−0.405, 0.1093, 0.1822, 0.1136
Never have contact with members of extended family (Scnenev)	−0.2763, 0.0746, 0.1243, 0.0775
Do not trust people in general (Scntnot)	−0.2741, 0.0740, 0.1233, 0.0768
Number of trips on travel day (Numtrps)	0.0182, −0.0049, −0.008, −0.0051
Personal growth (Pwbperg)	0.0905, −0.0244, −0.0407, −0.0254
Indirect partial effects for variables in thresholds	
Personal Well-being Index (PWI)	0.00, 0.0349, −0.0119, −0.0230
Daily kilometres of travel (kms)	0.00, 0.0006, −0.00019, −0.0004
Negative affect (NA)	0.00, 0.076, −0.0258, −0.0501
Age of individual	0.00, −0.00013, 0.00005, 0.00009

Note: The five marginal effects per attribute refer to the levels of the dependent variable ($Y = 0$, 1, 2, 3, 4).

being socially excluded increases quite a lot for a one-unit increase in Socomm. This suggests that there is a fair chance that they will be socially included. This positive effect is also strong for the trip rate (Numtrps). Conversely, there is a relatively high negative derivative on $Y = 0$ for Scneneev and Scntot.

The evidence in Table 4 suggests that where there is a positive and relatively high partial effect associated with the lower levels of Y, the explanatory variable contributes to reducing the extent of social exclusion. The strongest candidates are a person's connection with community (present), number of trips on travel day (increase), and personal growth (increase). The inverse is the case for those who do not trust people in general, and never have contact with members of the extended family.

In summary, Table 4 enables us to establish the degree of change in the probability of moving between the number of social well-being thresholds that a person fails to meet (as defined in Section 2), which is extremely useful in gauging which explanatory variables offer the greatest prospect of reducing social exclusion. The primary influence is via the direct partial effects; however, the indirect partial effects provide respondent-specific variations in the model's threshold parameters (in Table 3) that influence the level of utility (or disutility) associated with the switching points between each level of SOCEXA. The indirect effects are small for age, daily kilometres and PWI, despite the statistical significance of these effects in Table 3. However, there is a noticeable effect for NA when the positive and negative partial effects on the thresholds (see μ_{ij} in equation (15)) are compared, suggesting that an increase in NA will increase the probability of $Y = 1$ and reduce the probability of $Y = 2$ and 3, by 0.076. It has no effect on $Y = 0$.

While this result regarding high NA being associated with low risk of social exclusion was not predicted *per se*, it is not overly surprising. Correlates of 'Positive Affect' (PA) and NA are different and it is well known that PA and NA are related but independent constructs (Diener and Emmons, 1984). NA tends to be more highly correlated with ill-health and neuroticism rather than with positive health outcomes. Furthermore, NA and PA are not simply inverse constructs whereby if one has high PA then NA will be low. Over sufficient periods of time, it is possible to experience both NA and PA. The results of the current study suggest that NA (likely to be coupled with a reasonable level of PA) is important for preventing social exclusion. It has been found that NA does serve some important functions which include memory enhancement and strategic social behaviours such as being effectively persuasive in social contexts (Forgas, 2007). It is also important to note that while NA influences the extent to which one experiences social exclusion, it does not indicate the extent to which one feels socially included and connected. One would expect PA to predict positive social experiences.

6.0 Conclusions

The findings provide significant evidence to suggest that mobility is positively correlated with the likelihood of social inclusion among adults: higher trip-making implies less risk of social exclusion. Higher household income, connection with community, and personal growth (being open to new experiences) are also positively related to a lower risk of social exclusion. Low rates of contact with an adult person's close and extended families, conversely, are more likely to reflect an increased risk of social exclusion.

Using the statistically significant relationships between household income, trip rates, and the risk of social exclusion, the value of additional trips for the adult population sample has been estimated at just under $A20 per trip. This is about twice the value that would be implied by using generalised costs to infer values and over four times the value that results from using the generated traffic (50 per cent) rule. The authors are not aware of any prior direct estimates of the value of additional mobility derived in this manner. The values are estimated to decline with increasing household income levels. These new values are particularly relevant to the assessment of new public transport services, where benefit estimation has long been a question mark.

The recognition of randomness in the threshold parameters and the identification of systematic sources of heterogeneity in the mean threshold parameter estimate is an important extension of the existing ordered choice model. This paper has brought together the key contributions in the literature and extended them, in particular to ensure preservation of the ordering of thresholds in the context of random parameterisation of the thresholds. The specific application herein has highlighted the role of random thresholds and decomposition, suggesting that the generalised empirical model is a rich behavioural addition to the literature on ordered choice modelling.

References

Alsnith, R. and D. A. Hensher (2003): 'The Mobility and Accessibility Expectations of Seniors in an Ageing Population', *Transportation Research A*, 37(10), 903–16.

Argyle, M. and L. Lu (1990): 'The Happiness of Extraverts', *Personality and Individual Differences*, 11, 1011–17.

Australian Transport Council (2006): *National Guidelines for Transport System Management in Australia – 4: Urban Transport*, Commonwealth of Australia. Available on-line at http://www.atcouncil.gov.au/documents/ngtsm.aspx

Bell, D., G. Currie, J. Stanley, and M. Fletcher (2006): *Impacts of New Bus Services in Outer Suburban Melbourne – Final Report*, Report prepared for Bus Association of Victoria, Multi-Modal Transport Solutions in association with Monash University and Axiom consultants.

Bhat, C. R. and V. Pulugurta (1998): 'A Comparison of Two Alternative Behavioral Mechanisms for Car Ownership Decisions', *Transportation Research Part B*, 32(1), 61–75.

Bronfenbrenner, U. (1979): *The Ecology of Human Development: Experiments by Nature and Design*, Harvard University Press, Cambridge, MA.

Burchardt, T., J. LeGrand, and D. Piachaud (2002): 'Degrees of Exclusion: Developing a Dynamic, Multidimensional Measure, in Hills', in Le Grand, J. and D. Piachaud (eds.), *Understanding Social Exclusion*, Oxford University Press, Oxford, 30–43.

Cummins, R. A. (2001): 'Life Satisfaction: Measurement Issues and a Homeostatic Model', in Zumbo, B. (ed.), *Social Indicators and Quality of Life Research Methods: Methodological Developments and Issues, Yearbook 1999*, Amsterdam, Kluwer Academic.

Currie, G. and D. Delbosc (2009): Field Survey Report – Main Metropolitan Survey, Institute of Transport Studies (Monash University).

Currie, G., F. Gammie, C. Waingold, D. Paterson, and D. Vandersar (2005): 'Rural and Regional Young People and Transport: Improving Access to Transport for Young People in Rural and Regional Australia', Report to the National Youth Affairs Research Scheme, January.

Currie, G. and J. Stanley (2008): 'Investigating Links between Social Capital and Public Transport', *Transport Reviews*, 28(4), 529–47.

Department of Infrastructure (2005): *Guideline on Economic, Social and Environmental Cost–benefit Analysis*, Melbourne, Australia, Planning and Policy Division, Department of Infrastructure.

Diener, E. and R. A. Emmons (1984): 'The Independence of Positive and Negative Affect', *Journal of Personality and Social Psychology*, 47, 1105–17.

Diener, E., E. M. Suh, R. E. Lucas, and H. L. Smith (1999): 'Subjective Well-being: Three Decades of Progress', *Psychological Bulletin*, 125, 276–302.

Eluru, N., C. R. Bhat, and D. A. Hensher (2008): 'A Mixed Generalized Ordered Response Model for Examining Pedestrian and Bicyclist Injury Severity Level in Traffic Crashes', *Accident Analysis and Prevention*, 40(3), 1033–54.

Emmons, R. A. and E. Diener (1985): 'Personality Correlates of Subjective Well-being', *Personality and Social Psychology Bulletin*, 11, 89–97.

Ferrer-i-Carbonell, A. and P. Frijters (2004): 'How Important is Methodology for the Estimates of the Determinants of Happiness', *Economic Journal*, 114, 641–59.

Forgas, J. P. (2007): 'When Sad is Better than Happy: Negative Affect Can Improve the Quality and Effectiveness of Persuasive Messages and Social Influence Strategies', *Journal of Experimental Social Psychology*, 43, 513–28.

Golob, T. and D. A. Hensher (2007): 'Trawling the Past for Clues to the Future Mobility of the Elderly', *Journal of Transport Geography*, 15, 298–312.

Gordon, D., C. Pantazis, D. Patsios, S. Payne, P. Townsend, and J. Williams (2000): *Poverty and Social Exclusion in Britain*, Joseph Rowntree Foundation, York.

Gosling, S. D., P. J. Rentfrom, and W. B. Swann, Jr (2003): 'A Very Brief Measure of the Big-five Personality Domains', *Journal of Research in Personality*, 37, 504–28.

Greene, W. H. (2007): NLOGIT Version 4.0 Reference Manual, Econometric Software.

Greene, W. H. (2008): *Econometric Analysis*, 6th edn, Prentice-Hall.

Greene, W. H. and D. A. Hensher (2010): *Modeling Ordered Choices: A Primer and Recent Developments*, Cambridge University Press, Cambridge.

Harris, A. (2005): Transport and Mobility: Challenges, Innovations and Improvement, Seminar at Department for Victorian Communities, 27 May 2005.

Hong, S. and E. Giannakopoulos (1994): 'The Relationship of Satisfaction with Life to Personality Characteristics', *The Journal of Psychology*, 128, 547–58.

International Well-being Group (2006): Personal Well-being Index, Australian Centre on Quality of Life, Melbourne, Deakin University.

Levitas, R. (2000): 'What is Social Exclusion?' in Gordon, D. and P. Townsend (eds.), *Breadline Europe: The Measurement of Poverty*, Policy Press, Bristol, 357–83.

Loader, C. and J. Stanley (2009): 'Growing Bus Patronage and Addressing Transport Disadvantage – The Melbourne Experience', *Transport Policy*, 16, 106–14.

Long, D. A. and D. D. Perkins (2003): 'Confirmatory Factor Analysis of the Sense of Community Index and development of a brief SCI', *Journal of Community Psychology*, 31(3), 279–96.

Melbourne Institute of Applied Economic and Social Research (2007): Poverty Lines: Australia, June Quarter. Available on-line at http://melbourneinstitute.com/labour/inequality/poverty/default.html

Mollenkopf, H., F. Marcellini, I. Ruoppila, Z. Szeman, and M. Tacken (2005): *Enhancing Mobility in Later Life*, Amsterdam, ISO Press.

Obst, P. L. and K. M. White (2004): 'Revisiting the Sense of Community Index: A Confirmatory Factor Analysis', *Journal of Community Psychology*, 32(6), 691–705.

Putnam, R. (2000): *Bowling Alone: The Collapse and Revival of American Community*, New York, Vintage Books.

Rotter, J. B. (1966): 'Generalized Expectancies for Internal vs. External Control of Reinforcement', *Psychological Monographs*, 80, 1–28.

Ruini, C., F. Ottolini, C. Rafanelli, E. Tossani, C. Ryff, and G. Fava (2003): 'The Relationship of Psychological Well-being to Distress and Personality', *Psychotherapy and Psychosomatics*, 72, 268–75.

Ryff, C. D. (1989): 'Happiness is Everything, or Is It? Explorations on the Meaning of Psychological Well-being', *Journal of Personality and Social Psychology*, 57, 1069–81.

Social Exclusion Unit (2003): *Making the Connections: Final Report on Transport and Social Exclusion*, viewed November 2003. Available on-line at http://www.socialexclusionunit.gov.uk/publications/reports/html/transportfinal/summary

Spinney, J. E. L., D. M. Scott, and K. B. Newbold (2009): 'Transport Mobility Benefits and Quality of Life: A Time Perspective of Elderly Canadians', *Transport Policy*, 16, 1–11.

Stone, W., M. Gray, and J. Hughes (2003): 'Social Capital at Work: How Family, Friends and Civic Ties Relate to Labour Market Outcomes', *Research Paper No. 31*, Australian Institute of Family Studies, April.

United Kingdom Treasury (2003): *The Green Book: Appraisal and Evaluation in Central Government, Annex 5 – Distributional Impacts*, London, TSO.

Urry, J. (undated) Mobility and Proximity, Department of Sociology, Lancaster University. Available on-line at http://www.its.leeds.ac.uk/projects/mobilenetwork/downloads/urry1stpaper.doc

Vinson, T. (2004): *Community Adversity and Resilience: The Distribution of Social Disadvantage in Victoria and New South Wales and the Mediating Role of Social Cohesion*, Jesuit Social Services, Victoria, Australia, March.

Watson, D., L. A. Clark, and A. Tellegen (1988): 'Development and Validation of Brief Measures of Positive and Negative Affect: The PANAS Scales', *Journal of Personality and Social Psychology*, 54, 1063–70.