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Understanding Buy-in for Risky Prospects

Incorporating Degree of Belief into the ex-ante Assessment of Support for Alternative Road Pricing Schemes

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Abstract

This paper investigates support for road pricing reform within a referendum voting choice model. Central to this is how to identify believable ex-ante support for specific road pricing schemes. Our approach is centred on a referendum voting choice model for alternative road pricing schemes, with information that accounts for the degree of belief of the extent to which such schemes will make voters better or worse off. We find accounting for belief in the benefits results in sizeable reductions in the sensitivity to the levels of the charge, but quite small impacts on the sensitivity to revenue allocation.

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1.0 Introduction

Roads are possibly the most underpriced of all the public assets in terms of efficient user contributions. Regardless of whether some believe that governments should provide more road capacity to combat traffic congestion, it is an undeniable fact that if we provide more capacity under the existing road user pricing regimes and levels, more cars will use the roads, quickly using up the additional capacity. The great sadness about all of this is that there is a presumption that we all have rights to enter the traffic and delay all other motorists, yet not contribute to the true cost associated with delay and lost time — the 'tragedy of the commons'. The future of public transport is also linked to this tragedy of the commons, if one believes in the adage that 'to make public transport more attractive, we have to make the car less attractive'.

This paper develops a way of investigating community support for road pricing reform within the framework of referendum voting. The challenge that many jurisdictions face is persuading politicians and their advisers of the merits of road pricing reform. Central to this task is how to identify, in a convincing way, ex-ante support for specific road pricing schemes (defined in terms of a charge, a regime, and a revenue allocation plan), such that the evidence is believable. Our approach incorporates information that accounts for the degree of perceptually conditioned subjective belief of voters, with the alternative schemes making them better or worse off. Understanding degrees of belief in perceived benefits will provide critical guidance on ex-post support for a particular scheme when implemented, and hence can be used to identify the likely support both ex-ante and ex-post for specific road pricing schemes and promotional campaigns, in order to reduce the ambiguity and uncertainty of outcomes that impact individual voters and the community as a whole.

There is a burgeoning theoretical and empirical interest in how to get buy-in ex-ante for proposed road pricing schemes in cities exposed to growing levels of traffic congestion. We have reviewed this literature in Hensher and Li (2012). Two recent studies are examples where a specific emphasis is placed on the important role of revenue allocation in gaining support. Marcucci *et al.* (2005) use a citizen-candidate framework with a population composed of three groups differing in their income level, and show that road pricing policies are never applied when there is no redistribution of the resources in favour of other modes of transport or when the congestion of these types of transport is relatively high. The results suggest that the efficiency of the redistribution of resources from road to the alternative types of transport, as well as the fraction of the population that uses the road transport, are key factors in explaining the adoption of road pricing schemes.

De Borger and Proost (2012) use a simple majority voting model, and show that individual uncertainty with respect to modal substitution costs may imply that a majority votes against road pricing ex-ante, although a majority would have been in favour after its introduction ex-post. Moreover, if a majority is against road pricing ex-ante, there will also be no majority for organising an experiment that would take away the individual uncertainty. Their model also suggests that political uncertainty with respect to the use of the revenues corroborates the finding that ex-ante more voters will be against the introduction of tolls. Both types of uncertainty suggest that fewer voters are against road pricing when toll revenues are used to subsidise public transport than when they are redistributed to all voters. These results are consistent with recent empirical observations (see Hensher and Puckett, 2005, 2007; Eliasson *et al.*, 2009) on efforts to introduce road pricing, including the systematic rejection of road pricing in referenda, the more favourable attitudes towards road pricing after than before its introduction, and tying the revenues to support public transport.

The next section introduces the approach we have used to incorporate degrees of belief associated with making choices in general, as well as in the context of a choice experiment. We embed the degree of belief into a non-linear utility expression associated with the alternative charging regimes and revenue allocation propositions as a mixed logit choice model. We then discuss data needs and the design of a survey instrument that captures all the required empirical information and present voting choice models to identify the elasticities of interest in the presence and absence of accounting for perceptually conditioned subjective beliefs on scheme benefits. The paper concludes with suggestions for ongoing research.

2.0 Degrees of Belief and Road Pricing Schemes

This paper focuses on the voting (in a referendum) implications associated with recognising degrees of belief when assessing buy-in via a voting choice model to alternative road pricing schemes. In the current setting of road pricing reform, degrees of belief underlie decision weights that provide perceptual conditioning of subjective probability judgments associated with the extent to which each proposed road pricing scheme is perceived by a respondent as making them better or worse off. This evidence, derived directly as a numerical probability judgment, plays an important role in conditioning the marginal (dis)utility attached to the elements of a road pricing scheme (namely, the regime, the charge level, and revenue allocation). Such conditioning is aimed at increasing, ex-ante, the external validity of voting preferences in a referendum context.

We can obtain a numerical subjective probability belief judgment through direct questioning of individuals. For example, in terms of a proposed road pricing scheme:

> Suppose that the government were to introduce a distance-based car use charge of X c/km at congested (peak) periods and Y c/km at uncongested (off-peak) periods throughout Sydney [or in the Sydney Central Business District], together with a reduction in fuel excise of Tc/litre and a reduction in annual car registration charge of \$$W$ per annum.[1] Suppose also that revenue raised from a new road user charging scheme will be spent as follows — X per cent to improve public transport, Y per cent to improve existing and construct new roads, and W per cent to reduce income tax, instead of being put into the government's general revenue pool and spent as they desire (and to compensate private tollroad companies for the revenue loss from removal of tolls).
>
> To what extent do you think that each of these schemes will make you better (or worse) off (0 = not at all; 100 = definitely)?

[1]This can include the current fuel excise level.

This measure can be used to obtain probabilistic belief weights, denoted by $P(Z)$, where Z is a subjective belief response scale (0–100) associated with the road pricing scheme attributes in the utility expression for each alternative. It is well recognised in the psychology literature (see Tversky and Kahneman, 1992) that degrees of belief are implicit in most decisions whose outcomes depend on uncertain events. In quantitative theories of decision making such as subjective expected utility theory or prospect theory, degrees of belief are related to decision weights and are typically identified either by prescribed levels as part of alternatives in a choice experiment, or in a more direct manner using a linguistic device such as judgments of numerical probability. Such estimates are often viewed as an approximation to the degrees of belief implicit in decisions or preference revelation (see Fox, 1999). It is well recognised that numerical probability judgments are often based on heuristics that produce biases. One of the methods proposed to accommodate some aspects of such potential bias was the idea of a decision weight (Kahneman and Tversky, 1979) that accounts for the presence of perceptual conditioning in the way that information reported by decision makers or information offered to decision makers is heuristically processed. Specifically, the value of an outcome is weighted not by its probability, but instead by a decision (or belief) weight, $w(\cdot)$, that represents the impact of the relevant probability on the valuation of the prospect. $w(\cdot)$ need not be interpreted as a measure of subjective belief — a person may believe that the probability of a road pricing scheme making them better off is, for example, 0.5, but may afford this event a weight of more or less than 0.5 in the evaluation of a prospect.

A number of functional forms have been used in the literature to capture the extent of deviation between an obtained belief probability and a perceptually conditioned belief probability. We have chosen the popular form in equation (1), where $w(p)$ is the probability belief weight function, p_o is the subjective belief probability associated with the specific road pricing scheme, and γ is the probability weighting parameter to be estimated, which measures the degree of curvature of the belief weighting function. Equation (1) is an inverse S-shaped single-parameter weighting function with over-weighting of low belief probabilities, and under-weighting of medium to high belief probabilities for values of $0 < \gamma < 1$. This is the form originally proposed by Tversky and Kahneman (1992), which has been widely used in psychology and behavioural economics:

$$w(p_o) = \frac{p_o^{\gamma}}{[p_o^{\gamma} + (1 - p_o)^{\gamma}]^{(1/\gamma)}}. \tag{1}$$

In the empirical assessment of alternative road pricing schemes, we include revenue allocation as a crucial feature, in line with the evidence from the literature of its influence in engendering support or otherwise for a road pricing scheme (Hensher and Li, 2012). This is in addition to the description of a road pricing regime (for example, cordon or distance-based), and pricing levels for existing (for example, fuel, registration) and new charges. We speculate that the weighting parameter, γ, is likely to be different for the revenue allocation plan compared to the actual pricing scheme.

To complete the functional specification, we define a risk parameter α which reflects the presence of risk aversion, risk taking, and risk neutrality (depending on its empirical value) for accommodating risky decision making with respect to the road pricing schemes being assessed. The pricing levels associated with the new cordon or distance-based charges are represented as a constant *relative* risk aversion (*CRRA*) model form, defined by a general power specification (that is, $U = x^{1-\alpha}/(1-\alpha)$) (see Holt and Laury, 2002; Andersen *et al.*, 2012).

The attribute-specific representation in the utility expressions associated with each alternative road pricing scheme (rpcr) in the voting choice model is given in equation (2), where γ may empirically differ between the belief weight attached to the new pricing charges and the revenue allocation proposal:

$$U_{\text{rpcr}} = \beta_{\text{rpcr}}\{[W(P(Z)_{Q_i})\text{rpcr}^{1-\alpha} + W(P(1-Z)_{Q_i})\text{rpcr}^{1-\alpha}]/(1-\alpha)\}. \tag{2}$$

Q_i relates to beliefs in the context of the extent to which the charging scheme ($i = 1$) will make the voter better (or worse) off; similarly, for revenue allocation, Q_i ($i = 2$) relates to beliefs in the context of whether the proposed allocation of revenue will be perceived to make the voter better (or worse) off. There are also a number of other variables in the utility expression that are not specified this way, and are added in as linear in parameters. The presence of α and γ results in an embedded attribute-specific treatment in the overall utility expression associated with each alternative that is non-linear in a number of parameters. Only if $(1-\alpha) = 1$, and $\gamma = 1$, does equation (2) collapse to a linear utility function. We implement this framework with new data, including a stated choice experiment. Before doing so we set out the full likelihood function that accommodates the non-linear parameter form for the voter choice model.

3.0 A Mixed Multinomial Logit Model with Non-linear Utility Functions

A mixed multinomial logit (MMNL) model with non-linear utility functions is used to obtain parameter estimates for the voter choice model. The general form departs from a standard linear-in-parameters random utility model with utility functions defined over J_{it} choices available to individual i in choice situation t, and alternative m:

$$W(i,t,m) = U(i,t,m) + \varepsilon_{itm}, \quad m = 1,\ldots,J_{it}; t = 1,\ldots,T_i; i = 1,\ldots,N, \tag{3}$$

with the IID, type I extreme value distribution assumed for the random terms ε_{itm}. Conditioned on $U(i,t,m)$, the choice probabilities take the familiar multinomial logit form, as shown in equation (4):

$$\text{Prob}(i,t,j) = \frac{\exp[U(i,t,j)]}{\sum_{m=1}^{J_{it}} \exp[U(i,t,m)]}. \tag{4}$$

The utility functions that accommodate non-linearity in the unknown parameters, even where the parameters are non-random, are built up from an extension of the MMNL structure, along similar lines to Andersen *et al.* (2012), but with extensions to incorporate scale heterogeneity:

$$U(i,t,m) = \sigma_i[V_m(\mathbf{x}_{itm}, \boldsymbol{\beta}_i, \mathbf{w}_i)], \tag{5.1}$$

$$V_m(\mathbf{x}_{itm}, \boldsymbol{\beta}_i, \mathbf{w}_i) = h_m(\mathbf{x}_{itm}, \boldsymbol{\beta}_i) + \sum_{k=1}^{K} d_{km}\theta_k w_{ik}, \tag{5.2}$$

$$\boldsymbol{\beta}_i = \boldsymbol{\beta} + \boldsymbol{\Gamma}\mathbf{v}_i. \tag{5.3}$$

The various parts allow several degrees of flexibility. In equation (5.2), the function $h_m(..)$ is an *arbitrary non-linear function* that defines the underlying utilities (preferences) across alternatives. It is within $h_m(..)$ that we embed the attribute-specific belief weights and risk attitudes for the road pricing schemes. $\sum_{k=1}^{K} d_{km}\theta_k w_{ik}$ are the error components where the w_{ik} are normally distributed effects with zero mean, $i = 1, \ldots, M \leqslant J$ and $c_{km} = 1$, if m appears in utility function j, and θ_k is the standard deviation parameter.

Heterogeneity in the preference parameters of the model is shown in equation (5.3), where $\boldsymbol{\beta}_i$ varies around the overall constant $\boldsymbol{\beta}$ in response to unobservable heterogeneity in $\mathbf{v}_i$. The parameters of the distribution of $\boldsymbol{\beta}_i$ are the overall mean (that is, $\boldsymbol{\beta}$) and the Cholesky square root (lower triangle) of the covariance matrix of the random components, $\boldsymbol{\Gamma}$. The random components are assumed to have known, fixed (usually at zero) means, to have constant known variances (usually one), and to be uncorrelated. In the most common applications, multivariate standard normality would be assumed for $\mathbf{v}_i$. The covariance matrix of $\boldsymbol{\beta}_i$ would then be $\boldsymbol{\Omega} = \boldsymbol{\Gamma}\boldsymbol{\Gamma}$. Parameters that are not random are included in the general form of the model, by imposing rows of zeros in $\boldsymbol{\Gamma}$ including the diagonal elements. A non-random parameters model would have $\boldsymbol{\Gamma} = \mathbf{0}$ in entirety.

Parameters of the model are estimated by maximum simulated likelihood. The log likelihood function based on equations (3), (4), and (5) is given in equation (6):

$$\log L(\boldsymbol{\beta}, \boldsymbol{\Gamma}, \boldsymbol{\theta} \mid \mathbf{X}, \mathbf{y}, \mathbf{w}, \mathbf{v}) = \sum_{i=1}^{N} \log \prod_{t=1}^{T_i} P(i, t, j \mid \mathbf{w}_i, \mathbf{v}_i). \tag{6}$$

The conditioning is on the unobservables $\mathbf{w}$, $\mathbf{v}$ and the observables $\mathbf{X}_i$, $\mathbf{y}_i$, where $\mathbf{X}_i$ is the full data set of attributes and characteristics, $\mathbf{x}_{i,t,m}$, and $\mathbf{y}_i$ is a full set of binary indicators, y_{itm}, that marks which alternative is chosen, $y_{itj} = 1$, and which are not, $y_{itm} = 0$, in each choice situation. In full:

$$\text{Prob}(i, t, j) = \prod_{q=1}^{J_{it}} \left[\frac{\exp[U(i, t, j)]}{\sum_{m=1}^{J_{it}} \exp[U(i, t, m)]} \right]^{y_{itq}}. \tag{7}$$

To estimate the model parameters, it is necessary to obtain the log likelihood unconditioned on the unobservable elements. The unconditional log likelihood is:

$$\log L(\boldsymbol{\beta}, \boldsymbol{\Gamma}, \boldsymbol{\theta} \mid \mathbf{X}, \mathbf{y}) = \sum_{i=1}^{N} \log \int_{\mathbf{w}_i, \mathbf{v}_i} \prod_{t=1}^{T_i} [P(i, t, j \mid \mathbf{w}_i, \mathbf{v}_i) \times f(\mathbf{w}_i, \mathbf{v}_i)]\, d\mathbf{w}_i\, d\mathbf{v}_i. \tag{8}$$

Since the integrals do not exist in closed form, they are approximated, using simulation. The simulated log likelihood function is:

$$\log L_S(\boldsymbol{\beta}, \boldsymbol{\Gamma}, \boldsymbol{\theta} \mid \mathbf{X}, \mathbf{y}) = \sum_{i=1}^{N} \log \frac{1}{R} \sum_{r=1}^{R} \prod_{t=1}^{T_i} P[i, t, j \mid \mathbf{w}_i(r), \mathbf{v}_i(r)], \tag{9}$$

where $P[i, t, j|\mathbf{w}_i(r), \mathbf{v}_i(r)]$ is computed from equation (4) and equations (5.1) to (7) using R simulated draws, $\mathbf{w}_i(r)$, $\mathbf{v}_i(r)$ from the assumed populations. For optimisation, the derivatives of the simulated log likelihood function must be simulated as well (see Hensher *et al.* (2011) for details).

4.0 The Road Pricing Data Collection Approach

The survey instrument was an online computer assisted personal interview (CAPI) accessed via laptops used by interviewers who sat with the respondents to provide any advice that was required in working through the survey, while not offering answers to any of the questions. The two key elements of the survey are the belief questions and the voter choice experiment. The belief question was linked to each of the alternatives (excluding the status quo alternative) presented in the choice games, and was asked prior to the choice games.

The choice experiment consisted of three alternatives: two labelled alternatives representing a cordon-based charging scheme; and a distance-based charging scheme, randomly assigned to road pricing schemes 1 and 2 (see Figure 1 below), and the status quo. Each alternative was described by attributes representing the average amount of tolls and fuel outlaid weekly, the annual vehicle registration charge and the allocation of revenues raised to improve public transport, improve and expand upon the existing road network, to reduce income tax, to contribute to general government revenue, and to compensate tollroad companies for loss of toll revenue. The cordon-based charging scheme and a distance-based alternative were also described by either a peak and off-peak cordon-based charging amount, or a peak or off-peak per kilometre distance-based charge. Both non-status quo alternatives were also described by the year proposed that the scheme would commence.

A Bayesian D-efficient experimental design was implemented for the study. The design was generated in such a way that the cost-related attribute levels for the status quo were first acquired from respondents during preliminary questions in the survey, while associated attributes for the cordon-based and distance-based charging schemes were pivoted off of these as minus percentage shifts representing a reduction in such costs for these schemes. Pivoted attributes included average fuel costs and annual registration fees. Fuel costs were reduced by anywhere between 0 per cent and 50 per cent of the respondent-reported values, either representing no reduction in fuel taxes or up to a potential 100 per cent reduction. Registration fees were reduced to between 0 per cent and 100 per cent from the respondent-reported values (see Rose *et al.* (2008) for a description of pivot-type designs). Toll was only included in the status quo alternative, being set to zero for the non-status quo alternatives since it is replaced by the road pricing regime.

The allocation of revenues raised were fixed for the status quo alternative, but varied in the cordon-based and distance-based charging schemes over choice tasks. The allocation of revenue varied from 0 per cent to 100 per cent for a given revenue stream category. Within a charging scheme, the allocation of revenue was such that the sum had to equal 100 per cent across all possible revenue allocations.

The cordon-based charging alternative was also described by a peak and off-peak cordon charge. The peak charge varied between \$2.00 and \$20.00, while the off-peak charge varied between \$0.00 and \$15.00. Likewise, the distance-based charge was also described by two distance-based charging attributes, one for trips taken during peak periods and the second for off-peak trips. The per-kilometre charge for the peak period ranged from \$0.05 per kilometre to \$0.40 per kilometre, while the off-peak distance-based charge varied between \$0.00 and \$0.30 per kilometre. The ranges selected were based on those that we believed would contain the most likely levels if implemented. The

Table 1
The Choice Experiment Attribute Levels and Range

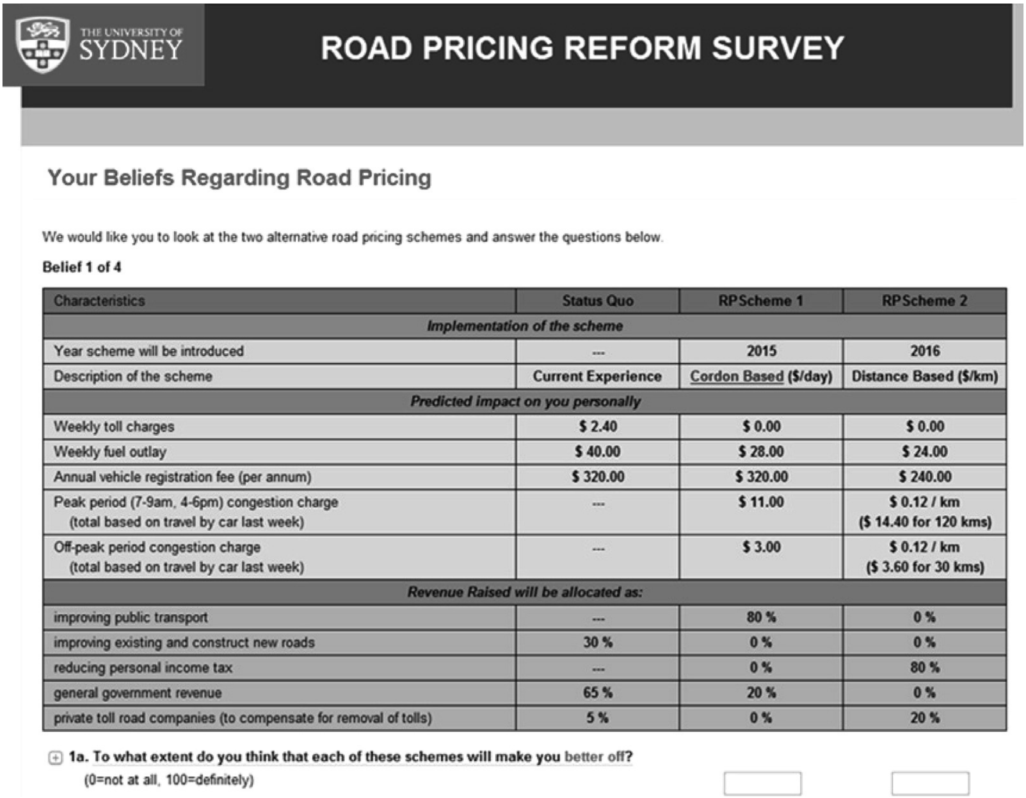
Attribute	*Status quo*	*Cordon-based scheme*	*Distance-based scheme*
Year scheme introduced	–	2013, 2014, 2015, 2016	2013, 2014, 2015, 2016
Average fuel per week	User reported level	0%, −10%, −20%, −30%, −40%, −50%	0%, −10%, −20%, −30%, −40%, −50%
Average toll per week	User reported level	$0.00	$0.00
Annual vehicle registration	User reported level	0%, −25%, −50%, −75%, −100%	0%, −25%, −50%, −75%, −100%
Peak cordon-based charge (per trip)	$0.00	$2.00, $6.50, $11.00, $15.50, $20.00	–
Off-peak cordon-based charge (per trip)	$0.00	$0.00, $3.00, $6.00, $9.00, $12.00, $15.00	–
Peak distance-based charge (per km)	$0.00	–	$0.05, $0.12, $0.19, $0.26, $0.33, $0.40
Off-peak distance-based charge (per km)	$0.00	–	$0.00, $0.06, $0.12, $0.18, $0.24, $0.30
% of funds allocated to public transport	0%	0%, 20%, 40%, 60%, 80%, 100%	0%, 20%, 40%, 60%, 80%, 100%
% of funds allocated to road infrastructure	30%	0%, 20%, 40%, 60%, 80%, 100%	0%, 20%, 40%, 60%, 80%, 100%
% of funds allocated to reducing tax	0%	0%, 20%, 40%, 60%, 80%, 100%	0%, 20%, 40%, 60%, 80%, 100%
% of funds allocated to general revenue	65%	0%, 20%, 40%, 60%, 80%, 100%	0%, 20%, 40%, 60%, 80%, 100%
% of funds allocated to private (toll) firms	5%	0%, 20%, 40%, 60%, 80%, 100%	0%, 20%, 40%, 60%, 80%, 100%

design was generated in such a way that the peak cordon-based and peak per-kilometre-based charges were always equal to or greater than the associated off-peak charges. Finally, the cordon-based and distance-based charging schemes were described by the year in which the scheme would be implemented. In each case, this was varied between 2013 (representing one year from the survey) and 2016 (representing a four-year delay from the time of the survey).

The attributes and the relevant attribute levels for all alternatives are shown in Table 1. Priors for the design were obtained from a pilot study consisting of nine respondents collected prior to the main field phase. The final design consisted of sixty choice tasks which were blocked into fifteen blocks of four choice tasks each. The blocking was accomplished by using an algorithm designed to minimise the maximum absolute correlation between the design attributes and the blocking column.

The final belief and choice screens are presented in Figures 1 and 2, with the boundaries of the proposed cordon-based charge area shown in Figure 3. Respondents had to be of voting age. The main survey of 200 residents was undertaken in April 2012 in the Sydney Metropolitan Area. A descriptive profile of the data is given in Tables 2a and 2b. Interviews took, on average, 46.2 minutes, but were as short as 12.37 minutes and as long as 88.5 minutes.

Figure 1
Illustrative Belief Screen



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ROAD PRICING REFORM SURVEY

Your Beliefs Regarding Road Pricing

We would like you to look at the two alternative road pricing schemes and answer the questions below.

Belief 1 of 4

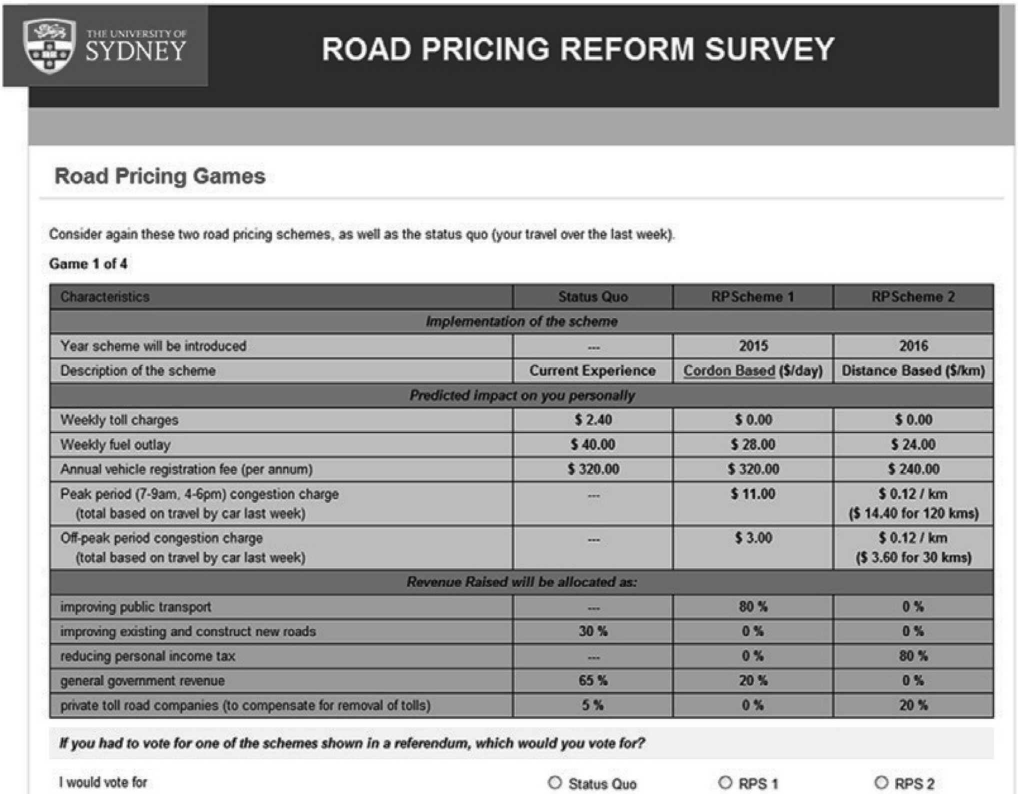
Characteristics	Status Quo	RPScheme 1	RPScheme 2
Implementation of the scheme			
Year scheme will be introduced	---	2015	2016
Description of the scheme	Current Experience	Cordon Based ($/day)	Distance Based ($/km)
Predicted impact on you personally			
Weekly toll charges	$ 2.40	$ 0.00	$ 0.00
Weekly fuel outlay	$ 40.00	$ 28.00	$ 24.00
Annual vehicle registration fee (per annum)	$ 320.00	$ 320.00	$ 240.00
Peak period (7-9am, 4-6pm) congestion charge (total based on travel by car last week)	---	$ 11.00	$ 0.12 / km ($ 14.40 for 120 kms)
Off-peak period congestion charge (total based on travel by car last week)	---	$ 3.00	$ 0.12 / km ($ 3.60 for 30 kms)
Revenue Raised will be allocated as:			
improving public transport	---	80 %	0 %
improving existing and construct new roads	30 %	0 %	0 %
reducing personal income tax	---	0 %	80 %
general government revenue	65 %	20 %	0 %
private toll road companies (to compensate for removal of tolls)	5 %	0 %	20 %

1a. To what extent do you think that each of these schemes will make you better off?
(0=not at all, 100=definitely)

The average weekly cost for the status quo is $66.86 (standard deviation of $45.76 and a maximum of $261.50); in contrast, the average associated with road price (RP) scheme 1 is $60.60 (standard deviation of $49.86 and maximum of $446.10), and for road price scheme 2 it is $58.87 (standard deviation of $50.28 and maximum of $415.70). When we difference each of the schemes against the status quo (see Figure 4), for RP scheme 1 we have an average of $6.26 in favour of the status quo (with a standard deviation of $32.50 and range from −$208.50 to $133.70), and for RP scheme 2 we have a mean difference of $7.99 in favour of the status quo, with a standard deviation of $32.53 and range from −$178.20 to $166.70. This indicates that the randomisation of the two RP schemes between the two non-status quo alternatives has resulted in similar profiles of each alternative across the sample, as expected.

Another way of presenting the RP schemes is to distinguish a cordon-based (CB) and a distance-based (DB) charging scheme. The CB schemes average $48.46 per week; in contrast, the DB schemes average $71.00 per week. The latter is close to the mean status quo cost of $66.86, whereas the CB proposals have a significantly lower weekly cost, clearly due to reduced fuel and registration charges, and no metropolitan-wide tolls.

Figure 2
Illustrative Voting Choice Screen


THE UNIVERSITY OF SYDNEY

ROAD PRICING REFORM SURVEY

Road Pricing Games

Consider again these two road pricing schemes, as well as the status quo (your travel over the last week).

Game 1 of 4

Characteristics	Status Quo	RPScheme 1	RPScheme 2
Implementation of the scheme			
Year scheme will be introduced	---	2015	2016
Description of the scheme	Current Experience	Cordon Based ($/day)	Distance Based ($/km)
Predicted impact on you personally			
Weekly toll charges	$ 2.40	$ 0.00	$ 0.00
Weekly fuel outlay	$ 40.00	$ 28.00	$ 24.00
Annual vehicle registration fee (per annum)	$ 320.00	$ 320.00	$ 240.00
Peak period (7-9am, 4-6pm) congestion charge (total based on travel by car last week)	---	$ 11.00	$ 0.12 / km ($ 14.40 for 120 kms)
Off-peak period congestion charge (total based on travel by car last week)	---	$ 3.00	$ 0.12 / km ($ 3.60 for 30 kms)
Revenue Raised will be allocated as:			
improving public transport	---	80 %	0 %
improving existing and construct new roads	30 %	0 %	0 %
reducing personal income tax	---	0 %	80 %
general government revenue	65 %	20 %	0 %
private toll road companies (to compensate for removal of tolls)	5 %	0 %	20 %

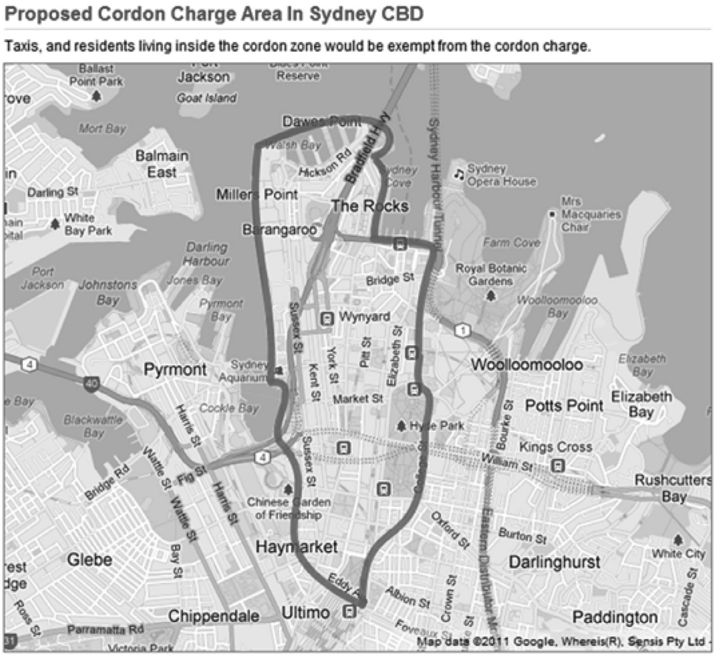
If you had to vote for one of the schemes shown in a referendum, which would you vote for?

I would vote for ○ Status Quo ○ RPS 1 ○ RPS 2

Over the range of RP schemes investigated, we see a marked support over the status quo situation, with only 19.6 per cent of the sample across four choice sets per respondent voting for maintaining the status quo. Thus, over 80 per cent of the time, the sample would vote for a new road pricing scheme. This is impressive and does suggest that there is some support for pricing reform where changes are also made in fuel (reducing for a mean of $46.12 to $34.60), registration (reducing from a mean of $680 per year to $340 per annum), and toll costs (reducing for a mean of $7.67 per week to zero) as part of the pricing reform package.

When we consider the extent to which respondents believe that they will be better off under a specific RP scheme, 61.8 per cent believe they will be better off under a proposed cordon-based reform initiative, while 49.5 per cent believe they will be better off under a proposed distance-based scheme. This evidence is encouraging and the contrast of these two percentages lines up well with the average weekly costs associated with the two schemes of $48.46 and $71.01 respectively. Clearly the ex-ante support must be determined in the context of a very specific RP scheme, which we undertake as a set of simulated scenarios once the voting choice model is estimated. Whether this ex-ante

Figure 3
The Location of the Cordon-charge Area



evidence would translate ex-post into support for road pricing if a referendum were held is unknown.

The distribution of revenues generated from congestion charging is the key to political support, as Goodwin (1997) claimed: 'discussion of road pricing without explicit attention to the use of revenue streams is inherently unlikely to be able to command a consensus in its support.' With regard to revenue distribution strategies, Small (1992) suggested that a package of travel allowances, tax reductions, and improved public transport be introduced as part of the buy-in plan. Goodwin (1989) proposed a combination of road improvements, public transport improvements, and the general fund of the city or state. The evidence from this study is that the sample supports 38.9 per cent of revenue raised being allocated to public transport improvements, 32 per cent to improving existing roads and construction of new roads, 16.1 per cent to reducing personal income tax, and the balance of approximately 13 per cent to compensating tollroad companies for loss of revenue and payments into government-consolidated revenue.

Two important features of the data are establishing the extent to which respondents are aware of what road pricing means and their familiarity with the road pricing debate. An indication was provided by 38 per cent of respondents that they are aware of what road pricing means, while 22.6 per cent expressed familiarity with the debate. In addition, over 91 per cent of respondents indicated that they would support a road pricing reform trial, and furthermore that it would only take, on average, a 9 cents per

Table 2a
Descriptive Profile of Sample

Status quo variables	*Mean*	*Std. Dev.*	*Min*	*Max*
Total cost (per week)	66.86	45.76	0	261.5
Fuel cost (per week)	46.12	34.99	0	200
Tolls per week	7.67	14.63	0	100
Vehicle registration per annum	679.65	464.99	0	3,200
Alternative voted for if a referendum on road pricing (%)	19.6		0	1
Alternative chosen as best for respondent (%)	20.3		0	1
Alternative chosen is seen as best for the community (%)	16.8		0	1
Cordon road pricing scheme variables	*Mean*	*Std. Dev.*	*Min*	*Max*
Total cost (per week)	48.46	36.69	0	243.9
Fuel cost (per week)	34.46	27.25	0	180
Tolls per week	0	0	0	0
Vehicle registration per annum	339.9	377.38	0	3,200
Peak charge (7–9 a.m., 4–6 p.m.) $ per entry	11.05	6.37	2	20
Off-peak charge $ per entry	5.83	4.50	0	15
Cordon charges per week	7.47	17.05	0	132
Peak period weekly cordon cost outlay	3.58	9.75	0	83.5
Off-peak period weekly cordon cost outlay	3.89	9.58	0	84.1
Alternative voted for if a referendum on road pricing (%)	49.6		0	1
Alternative chosen as best for respondent (%)	50.6		0	1
Alternative chosen is seen as best for the community (%)	49.5		0	1
Road pricing scheme is acceptable (%)	76.4		0	1
Revenue allocated to public transport (%)	21.2	27.5	0	100
Revenue allocated to existing and construct roads (%)	18.4	26.5	0	100
Revenue allocated to reduce personal income tax (%)	20.9	26.3	0	100
Revenue allocated to private tollroad company (%)	18.9	29.2	0	100
Revenue allocated to general govt revenue (%)	20.7	27.6	0	100
Belief that the road pricing scheme will:				
make you better off	0.62	0.33	0	1
be fair for the community	0.24	0.33	0	1
be effective in reducing traffic congestion	0.27	0.33	0	1

km peak charge to encourage a significant switch in car travel out of the peak periods (7–9 a.m. and 4–6 p.m. weekdays).

5.0 Voter Choice Models

The voting choice models are summarised in Table 3. Both models allow for preference heterogeneity and risk attitude, the latter only included for the new distance- or cordon-based

Table 2a
Continued

Distance-based road pricing scheme variables	*Mean*	*Std. Dev.*	*Min*	*Max*
Total cost (per week)	71.01	58.44	0	446
Fuel cost (per week)	34.62	28.65	0	200
Tolls per week	0	0	0	0
Vehicle registration per annum	342.4	374.2	0	3,200
Peak charge (7–9 a.m., 4–6 p.m.) $ per week given weekly kilometres	15.12	22.01	0	160
Off-peak charge $ per week given weekly kilometres	14.68	25.26	0	234
Peak period distance-based cost per km ($/km)	0.225	0.120	0.05	0.40
Off-peak period distance-based cost per km ($/km)	0.101	0.097	0	0.3
Alternative voted for if a referendum on road pricing (%)	30.6		0	1
Alternative chosen as best for respondent (%)	29.1		0	1
Alternative chosen is seen as best for the community (%)	33.6		0	1
Road pricing scheme is acceptable (%)	55.9			
Revenue allocated to public transport (%)	21.1	30.5	0	100
Revenue allocated to existing and construct roads (%)	18.6	27.2	0	100
Revenue allocated to reduce personal income tax (%)	22.5	28.4	0	100
Revenue allocated to private tollroad company (%)	20.5	26.9	0	100
Revenue allocated to general govt revenue (%)	17.3	26.48	0	100
Belief that the road pricing scheme will:				
make you better off	0.49	0.349	0	1
be fair for the community	0.21	0.314	0	1
be effective in reducing traffic congestion	0.27	0.334	0	1

Note: Tables 2a and 2b can be merged as needed.

charging components. Model 1 also includes the belief weights that condition the marginal utility or disutility weights attached to the new distance- or cordon-based charging components, and the revenue allocation categories. These models are non-linear in the risk attitude and belief functions (see equation (2)). We investigated the potential role of awareness and familiarity, but found that these influences were not statistically significant in the presence of the significant influences in Table 3. Notably, there was a strong correlation between belief, awareness, and familiarity, which may explain this non-significance.

The overall goodness of fit of the model with embedded belief is significantly better than the model that ignores the role of belief. All parameter estimates are significant at the 10 per cent or better level of statistical confidence, with the majority of parameters being significant at well above the 5 per cent confidence level.

The difference in the probability weighting parameter γ which measures the degree of curvature of the belief weighting function in Model 1, associated with belief conditioning for the new charging level and the revenue allocation, is an important finding, suggesting that as gamma approaches 1, the function is linear in the belief probability weighting. A gamma less than 1 in the positive domain will tend to lead to greater divergence at the extreme range of the probability distribution between the reported belief probability and

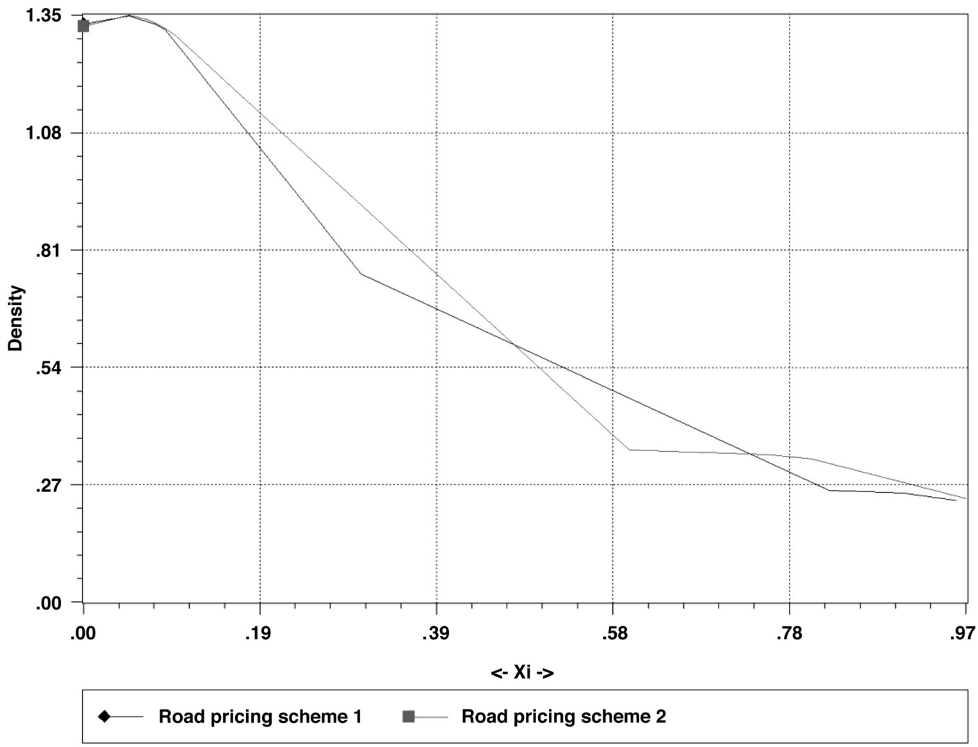
Table 2b
Descriptive Profile of Sample

Other descriptive data	*Mean*	*Std deviation*	*Min*	*Max*
Peak kilometres per week	70.68	88.58	0	400
Off-peak kilometres per week	145.9	143.6	0	977.5
Proportion of weekly kilometres in peak	0.297	0.269	0	0.99
Weekly hours travelling by car and motorbike	7.60	6.68	0	50
Weekly CBD trips	1.85	3.48	0	18
Preferred revenue allocated to public transport (%)	38.86	18.50	0	100
Preferred revenue to existing and construct roads (%)	32.03	14.44	0	70
Preferred revenue to reduce personal income tax (%)	16.06	16.83	0	100
Preferred revenue to private toll road company (%)	6.20	8.11	0	50
Preferred revenue to general govt revenue (%)	6.86	8.41	0	30
Extent of awareness of what road pricing means (%)	38.03	29.24	0	100
How familiar are you with the debate on road pricing (%)	22.63	27.09	0	100
Confidence in public sector allocating revenue as you indicated (%)	22.32		0	100
Would support a road pricing trial (%)	91.8		0	100
Cents per km to switch from peak travel if price selected (84% sample)	9.06	5.02	2	15
Amount spent per week on fuel ($)	46.12	34.98	0	200
Amount spent per week on tolls ($)	7.67	14.63	0	100
Amount spent per week on public transport fares ($)	13.02	25.70	0	96
Annual vehicle registration excl insurances ($)	679.6	464.8	0	3200
Percentage of fuel and toll costs paid by respondent (%)	84.6		0	100
Percentage of fuel and toll costs paid by business respondent owns (%)	3.53		0	100
Percentage of fuel and toll costs paid by another business (%)	8.88		0	100
Number of privately registered cars in household	1.85	1.01	0	5
Number of household business registered cars in household	0.19	0.83	0	9
Number of other business registered cars in household	0.11	0.31	0	1
Age of respondent	50.6	14.2	30	70
Annual personal gross income	74,225	53,167	10,000	250,000
Male	35.6		0	1
No. of people in household 17 years plus	2.79	1.13	1	7
No. of people in household 11–17 years old	0.24	0.58	0	3
No. of people in household under 11 years old	0.31	0.71	0	4
No. of people in household who hold a valid driver's licence	2.53	1.06	0	4
Survey interview time (mins)	46.2	12.37	11.4	88.5

the perceptual conditioned belief probability, in contrast to situations where gamma exceeds 1.

The mean response on the subjective belief scale is 0.56, with a standard deviation of 0.34, and a skewness of −0.25. The perceptually conditioned belief weight distribution

Figure 4
Difference in Weekly Cost Outlay: Status Quo Minus Road Pricing Scheme



has a mean of 0.30 (standard deviation of 0.30 and skewness of 0.69) related to the new distance- and cordon-based charging levels, and 0.35 (standard deviation of 0.39 and skewness of 0.55) for revenue allocation.

Given the two estimated parameters for gamma related to the new distance- and cordon-based charging levels and the revenue allocation plan, the resulting belief weights have been obtained using the functional form from Tversky and Kahneman (1974), given in equation (2). A plot of the reported subjective belief response probability against the perceptually conditioned belief weights is given in Figure 5. The findings are similar to what are reported in the many prospect theory studies in respect of decision weights.

At low levels of subjective belief probability, up to 0.3, we find that the perceptual conditioned belief probability is higher for the belief function associated with the new classes of charging; however, as we move beyond 0.3, the perceptually conditioned belief probability is lower than the subjective response. This suggests that there is a tendency to underestimate the belief probability at low levels of subjective belief probabilities (up to 0.3) and to overestimate the subjective belief response at higher levels of probability (over 0.3), with the greatest gap at around 0.9. Likewise, when considering the belief weights associated with revenue allocation, there is a tendency to overestimate the

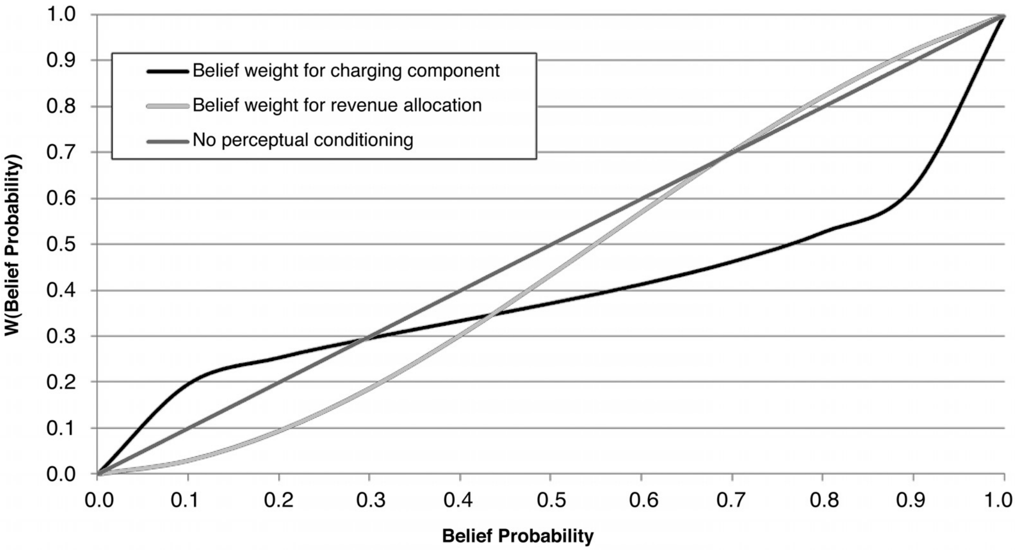
Table 3
Summary of Voting Choice Models: 800 Observations (200 Respondents)

Attributes	Model 1 (embedded belief)		Model 2 (no account for beliefs)	
	Parameter	t-ratio	Parameter	t-ratio
Mean of random parameters:				
Current cost elements (fuel, registration, tolls) (per week)	−0.0412	−4.31	−0.05534	−5.42
New distance- or cordon-based charging (per week)	−0.0969	−3.04	−0.2258	−6.24
Per cent of revenue allocated to:				
improving public transport	0.0619	7.24	0.0222	5.52
improving existing and construct new roads	0.0376	6.11	0.0142	3.71
reducing personal income tax	0.0472	6.40	0.0152	4.23
Standard deviation or spread of random parameters:				
Current cost elements (fuel, registration, tolls) (per week) (t, 2)	0.0824	4.31	0.1107	5.42
New distance- or cordon-based charging (per week) (lognormal)	0.2027	4.00	0.1991	4.87
Improving public transport (lognormal)	0.0403	3.03	0.0220	3.00
Improving existing and construct new roads (lognormal)	0.0233	1.81	0.0191	2.15
Reducing personal income tax (lognormal)	0.0385	2.95	0.0136	1.51
Non-random parameters:				
Alpha (risk attitude)	0.2749	1.68	0.6649	13.2
Gamma for new distance- or cordon-based charging (belief conditioning)	0.5268	2.11	–	–
Gamma for revenue allocation (belief conditioning)	1.5646	4.13	–	–
Status quo constant	−0.7848	−1.01	−2.2188	−2.36
Male (1,0)	1.0318	1.60	1.3288	1.77
Annual personal income ('000s)	−0.0117	−1.81	−0.0112	−1.51
Total one-way trips per week	−0.0533	−2.31	−0.0539	−2.08
Error component:				
Sigma (non-status quo alternatives)	2.9510	5.91	3.4003	6.19
Model fit:				
Log-likelihood (0)	−878.89		−878.89	
Log-likelihood at convergence	−568.58		−623.04	
Adjusted pseudo R^2	0.353		0.291	
AIC (sample adjusted)	1.456		1.593	

subjective response belief probabilities up to 0.7 with a negligible difference (albeit marginally underestimated) over 0.7.

It is clear from this evidence that perceptual conditioning does matter, especially at the very low and very high probabilities, suggesting that perceptual conditioning moves the belief probabilities towards 0.5 in comparison to what is reported. That is, the extremes of the subjective belief distribution are suppressed as a result of perceptual conditioning for the new distance- and cordon-based charging levels. For revenue allocation the opposite occurs, with perceptual conditioning tending to downscale the subjective

Figure 5
Belief Weights and Perceptual Conditioning



belief response probabilities throughout the entire distribution, up to 0.7, and no effect beyond 0.7.

The belief weighting function is a transformation of a stated degree of belief, and as such there is the potential risk of endogeneity bias (EB). EB can arise from a number of sources such as measurement error, missing attributes, and simultaneity; it is observed when a specific variable included in the observed effects is correlated with the error term associated with the utility expression containing the explanatory variable of interest. To ensure that the belief weighting function is purged of its endogeneity bias (that is, the part that is correlated with the random error component), we undertook two tasks. First, we tested the extent to which the belief weight has systematic influence on the standard deviation of the error component; and second, we identified other exogenous variables that are correlated with the belief weight, but not with the error component that could be used as instrumental variables, or simply as evidence of no endogeneity bias. An important finding is that the belief weight transform purges the correlation compared to the use of the stated belief response, effectively eliminating the possibility of endogeneity bias. We included the belief weights in the error component decomposition and found that they had t-values of -0.04 and -0.18 respectively for the new charges and the revenue allocation belief functions, which suggests that the belief weights have no correlated influence on the error components. Hence we conclude that there is no statistically observed evidence of endogeneity bias.

As expected, there is a greater variance in the unobserved effects associated with the road pricing scheme alternatives, captured by the statistically significant sigma parameter for the error component associated with the two road pricing alternatives. This is a plausible finding, suggesting that there is greater unobserved heterogeneity within the

Table 4
Mean Direct Elasticities of Probability of Voting Choice

Attribute of road pricing scheme	*Model 1 (embedded belief)*	*Model 2 (no account for beliefs)*
Current cost elements (fuel, registration, tolls) (per week)	−0.463	−0.662
New distance- or cordon-based charging (per week)	−0.062	−0.273
Improving public transport	0.156	0.139
Improving existing and construct new roads	0.107	0.092
Reducing personal income tax	0.135	0.116

voting population, as represented by the sample, in respect of the role of unobserved influences on the probability of voting for the road pricing schemes in comparison to voting to stay with the status quo.

The inferred mean direct elasticities of probability of voting for a road pricing scheme with respect to a specific attribute associated with a proposed road pricing scheme are summarised in Table 4. The most revealing finding is that when account is taken of the belief that respondents have in the extent to which a road pricing scheme will make them better or worse off, and after the subjective belief response data on the 0–100 scale is adjusted for perceptual conditioning, the mean estimate of the impact of a percentage change in the charge is considerably smaller than would be the case if beliefs were not accounted for. For the way that the raised revenue is allocated, the mean estimate of the impact of a percentage change in revenue allocation is lower when beliefs are accounted for, but the difference is quite small.

To illustrate the likelihood of a vote in a referendum for a specific road pricing scheme, we have selected a number of schemes that might represent the range of options under consideration by government. Model 1 with embedded belief is applied to the sample, using a simulator that allows for random parameters, and all non-linearity in belief and risk attitudes. These are summarised in Table 5, together with the predicted proportion of the population that would vote for the scheme based on the sample being representative of the voting population.

The findings show clearly that a cordon-based charge in the CBD is a sensible initial scheme to introduce, since it is predicted ex-ante to obtain more than a 50 per cent (that is, 62.4 per cent) vote when the daily peak entry charge is \$8 and the off-peak charge is \$3, and 100 per cent of funds are allocated to public transport improvements (RP scheme 12). This reduces to 60.9 per cent when the revenue is allocated 50:50 to public transport and road improvements (RP scheme 13). Distance-based charging (RP schemes 5–7, 9–11) is clearly less popular, with the highest percentage voting for a scheme in the examples in Table 5 being 32.2 per cent. A particularly important finding is that when the revenue allocation is recognised in conjunction with distance-based charging, the support increases from 17.6 per cent to between 25.5 and 27.1 per cent (depending on the revenue allocation plan). The evidence reinforces the view in the growing literature that how the revenue is allocated is critical in obtaining buy-in to road pricing proposals (see Hensher and Li, 2012). What we have been able to do for the first time is identify the very specific role of revenue allocation in influencing, ex-ante, the voting intentions of the population.

Table 5

Predicted Support for a Road Pricing Scheme under a Referendum: Illustrative Scenarios

	RP scheme												
Attribute of RP scheme	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*
Current cost elements (fuel) $/km	SQ	SQ	SQ	0.5SQ	SQ	SQ	SQ	0.5SQ	0.5SQ	0.75SQ	SQ	SQ	SQ
Current cost elements (registration) per annum	SQ	SQ	SQ	SQ	SQ	SQ	SQ	0.5SQ	0.5SQ	0.75SQ	SQ	SQ	SQ
New distance-based charging ($/km) — peak	–	–	–	–	5	5	5	–	8	5	3	0	0
New distance-based charging ($/km) — off-peak	–	–	–	–	0	0	0	–	3	3	0	0	0
New cordon-based charging ($/day) — peak	10	20	20	20	0	0	0	0	0	0	0	8	8
New cordon-based charging ($/day) — off-peak	5	5	10	10	0	0	0	0	0	0	0	3	3
Improving public transport revenue allocation (%)	0	0	0	0	0	50	100	0	100	100	100	100	0
Improving existing and construct new roads revenue allocation (%)	0	0	0	0	0	30	0	0	0	0	0	0	0
Reducing personal income tax revenue allocation (%)	0	0	0	0	0	20	0	0	0	0	0	0	0
Predicted voting support	**47.7**	**46.6**	**45.1**	**58.1**	**17.6**	**25.5**	**27.2**	**79.1**	**9.5**	**10.3**	**32.2**	**62.4**	**48.9**

6.0 Conclusions

The substantive empirical findings offer new evidence on the ex-ante probability of voting for a range of road pricing schemes, accounting for the regime (that is, cordon- or distance-based), the charge level (fixed per time of entry or cents per km by peak and off-peak times), and how the revenue raised is allocated. There exists, to varying degrees, ex-ante support (or buy-in) for specific road pricing schemes if they were subject to a referendum vote. It is clear that how the revenue is allocated has a significant influence on the level of support, and that introducing a cordon-based charging scheme in the CBD that has different fixed charges for the peak and off-peak is a wise transitional strategy to a full roll-out in the future of a metropolitan-wide distance-based charging scheme.

This paper also promotes a view that subjective beliefs about the extent to which a road pricing scheme will make someone better or worse off should, after perceptual conditioning, be included in a voting choice model, as a way of recognising the role of belief in voting outcomes. The evidence herein highlights the important role of belief, and in particular how its influence increases the support for voting for a road pricing scheme compared to ignoring such relevant information.

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