CAN PERSONALITY FACTORS IN MODE CHOICE AFFECT THE OUTCOME OF THE TRANSPORT INVESTMENTS DECISION MAKING PROCESS? A CASE STUDY IN THE CHILEAN CONTEXT

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ABSTRACT

Decision making on transport investments based on cost benefit analysis, relies strongly upon accurate demand forecasting in order to properly capture the users’ benefits. For that reason, we need proper methods, models, and data collection techniques that could better predict, for example, how personality factors can influence travel demand.

In this work, we study the role of personality factors on demand forecasting and the outcome of the consequent cost-benefit analysis. Data include transport mode level of service attributes, socio-demographic information and personality indicators of attitude, affection and habit. These data are used to estimate two demand models. One of the models does not incorporates personality factors whilst the other does it through a latent variables approach when necessary. Different model specifications are studied in this case, finding that the one incorporating just the habit indicator performs better in statistical terms. These models are used to forecast demand levels for different transport modes, when assessing the implementation of public transport exclusive lanes in the city of Concepcion, Chile.

After applying the Chilean cost benefit analysis methodology, results show that the net benefit and other economic indicators perform worse when personality factors are considered in the modelling. Actually, when these attributes are not taken into account, demand level and benefits are larger. As a consequence, the omission of these attributes might lead to an overestimation of demand levels and project benefits, altering the efficient outcome of the decision making process. As a consequence, it seems that instrumental, socio demographic and personality attributes should be considered into the modelling of demand when studying transport public investments.
1. INTRODUCTION

Decision making on transport investments, based on cost benefit analysis, relies strongly on demand levels. In fact, success of transport investments, resting on the capturing of users’ benefits, will depend to some extent on the accuracy of demand forecasting [1]. This fact has derived in an important development of methods, models, and data collection techniques oriented to predict passengers and traffic volumes with exactitude under different operational conditions [2].

In this work, we study the role of personality factors on demand forecasting, using a latent variables approach for their incorporation into the modeling, and the outcome of a cost benefit analysis. It has already been found that these factors might affect demand modeling and estimations [3], requesting their consideration in the modelling and forecasting processes.

This study uses two merged datasets of transport mode revealed preferences to estimate two demand models. Data include modes’ level of service attributes, travelers’ socio-demographic information and personality indicators of attitude, affection and habit. One of the estimated models does not incorporates personality factors whilst the other does through the latent variables approach; the best estimated alternative model was the one incorporating the habit indicator, performing slightly better than one considering the attitude and habit variables. These models are used to forecast the demand levels for two main transport modes: buses and cars, when assessing the implementation of public transport exclusive lanes in the Concepcion district, Chile. This intervention is compared with the base alternative, which consists of an operational improvement of the corridor.

It was found that, after applying the Chilean cost benefit analysis methodology, the net benefit and other economic indicators perform worse when personality factors are taken into account from the modelling. Actually, when these attributes are not taken into account, demand levels are larger, implying that the omission of these attributes might lead to an overestimation of demand levels and project benefits, altering the efficient outcome of the decision making process.

The paper is organized as follows. Next section contains a description of the cost benefit analysis methodology used in Chile and some antecedents on the incorporation of personality factors in the study and modelling of individuals’ behavior. Section three has a description of the case study, whereas section four provides information about the demand models for the situation without and with the personality attributes. Cost benefit analysis results are shown and analyzed in section five, whilst comments and conclusions are given in the last section.
2. BACKGROUND

2.1. Cost benefit analysis

Decision making based on cost benefit analysis (CBA) looks for the maximization social welfare, with a theoretical root from Welfare Economics [4]. Attributes describing the interventions under evaluation, their prices, and other data are identified and quantified for each alternative being considered, including the base situation, for a given evaluation horizon. Different indicators are generated to guide the decision making process.

CBA has been criticized due to simplifications and assumptions used during its application [1]. One of the main challenges is related with the need of accurate estimations of the number of users being benefited by the interventions under assessment. Demand levels might be usually overestimated, leading to the approval of interventions which after an ex-post analysis might have proved to be non-socially desirable [5]. To cope with this pitfall, many advances have been carried out for a long period to create and identify methods, models and techniques for data collection, looking for a better forecasting [2].

CBA for transport investments in Chile rest on a methodology based on a resources use-based approach by calculating social prices of mainly operational costs and times. Land expropriation and investment levels, as well as qualified and non-qualified labor are also quantified and assessed. Different evaluation horizons are defined depending on the type of project; spatial and temporal impacts as well as the investment amount are considered for this. There are no explicit guidelines regarding demand forecasting, although there is an explicit recognition of the existence of a demand elasticity for those projects that generate changes in prices and level of service variables [6]. All or some of the stages of the four step model are requested to be considered subject to the type of intervention, depending on the horizon of evaluation. This can be requested by the authority or agreed between the public officers and the consultant developing the study.

2.2. Incorporation of personality factors in travel demand models

Two strands of development on travel demand modeling are important for this study. The first one is related with the explicit recognition of the role of personality factors on travel behavior. Aspects such as attitude, affection, habit, and social dimensions have been identified as key factors affecting conduct [7, 8, 9]; theoretical frameworks from Social Psychology have been vital on these advances [10, 11].

Attitude is referred as the importance and value that an object or situation might have for someone [12]. It can be positive or negative and can be measured using Likert scales. Affection corresponds to the emotional impact that can be triggered by an object [13], being measured using semantic differentials. The social dimension of the travel behavior can be described through the role (what you are supposed to do given your position in a group), the norm (what you do given what others do in your group), and the self-concept (what you do given your self-perception) [14]. Different instruments are used to measure these dimensions. Finally, habit is defined as a non-reasoned conduct, without too much deliberation [15];
response-frequency questionnaires are used to measure habit. It is important to remark that a repeated behavior might not constitute habit if there is deliberation in the process of generating the conduct. All these factors can be described as latent variables, since they cannot be measured straightforward, with the exception of but habit when using response-frequency questionnaires.

The second line of development linked with making explicit the personality factors in the modeling are hybrid modeling technique, which allow the specification to include latent variables, such as the ones previously described, into the transport mode choice models. Although sequential approaches are feasible to model these latent variables, simultaneous estimation techniques are preferred, jointly determining all coefficients for latent and non-latent variables [16, 17, 18]. Open source codes are now available for the estimation of these models, using simulated likelihood techniques [19]. Figure 1 illustrates how these latent variables are included in the utility maximization framework when modelling modal split.

An explanatory variable would correspond to the level of service, for instance. A latent variable would be the affection level reported through an indicator, which would be the measurement of that variable using a specific scale (semantic differential). Preferences or choices can be captured through revealed or stated preferences. Notice that the utility is itself a latent variable, described using the explanatory and latent variables. \( \varepsilon, \eta \) and \( v \) are error terms, reflecting measurement error, omission of variables or functional specification errors. The structure of these error terms will yield to the different demand models [2, 18, 19].

3 Case study description

The impact of personality variables on decision making regarding transport investments and management was studied in the Collao area, Concepcion, Chile. Different interventions were identified to tackle severe congestion problems in the area, especially those related to segregate public and private transport lanes [20]. Figure 2 shows the study area and the location of the intervention. The pointed (blue) line defines the limits of the study area, whereas the thick (red) line corresponds to the location of the intervention. The project is almost 2 kilometers long.

The social assessment of the interventions consider the pre-evaluation of up to six alternatives [20]. One of these alternatives was chosen for further development, in terms of a better accuracy of investment levels and engineering design. The criteria for the selection was based on the net present value and internal rate of return obtained after the pre-evaluation. This selected alternative will be used in this work for further analysis, since there is more information regarding the investment level and operational costs.

The alternative under study considers two sections (Tramo 1 and Tramo 2) as depicted in Figure 3. In the first section (Tramo 1), there are six lanes: two lanes for public transport and four lanes for private cars, built into two streets. Public transport and two of the private lanes run on one of the streets; besides there is a bike path along. The second section (Tramo 2) has four lanes; two for public transport and two for the private one; there is also a bike path along. This configuration of lanes in the corridor is related with the activity system in the
sector and the connected areas, which is mainly residential (low and medium income households). Segregation of private, public and non-motorized transport allows for each mode to increase their mean speed as well as safety levels, when compared with a mixed traffic condition.

The social evaluation carried out by the authority considered a fixed origin destination matrix by mode, considered to be a conservative assumption. Changes on the modal split were not considered in spite of the modification of travel of times, frequencies and operational costs. These assumptions are relaxed in this work, introducing changes on the modal split, for those users who are able to change mode. We remark that, in the study’s area context, very low income groups are public transport captives, whilst medium income groups tend to be car dependents. The available sociodemographic information allowed us to identify those groups which might shift from mode. In the next section, the travel demand models are presented.

4 Travel demand data and modelling

The modal split estimation was carried out using two joint data bases, collected in 2011 and 2012 in the Collao sector, where the intervention under analysis is proposed [21, 22]. Adult individuals were face to face interviewed in both surveys, in a revealed preference approach. Socio-demographic information and personality factors (attitude, affection and habit) were also gathered. Trip data referred to their first trip in the morning. The total number of valid responses for model estimation was of 304; 81 are from the first exercise, and 223 belong to the second one. Even though this sample size might be deemed as small, it is good enough for the prospective analysis carried out in this research. Estimated demand models can detect the role of level of service and personality factors on mode choice, as shown later.

All 304 interviewed people had the possibility of choosing among at least two available transport modes to develop their declared trip. Table 1 shows aggregated indicators describing the whole set of interviewed people, including income level and transport mode being used. As discussed before, lower income segments use more public transport (buses and shared taxis), whereas travelers with higher income are car users (as driver or accompanying person). The majority of the respondents in the sample were public transport users (186 out 304).

Model estimation was carried in successive steps. The fist model, named traditional, takes into account instrumental and socio-demographic data. The following models incorporate personality factors, using the latent model approach mentioned before. Table 2 shows the best fit models, for the traditional and advanced approaches, to be used in the modified social assessment. A full description of the model estimation process can be found in [23]

Utility functions were specified linear in coefficients and attributes, when estimating multinomial logit models. Cost was divided by income when introduced into the model. Since habit was measured using the frequency response questionnaire, which provides a continuous way to measure it, there was no need to use the latent variables approach for these variables. Furthermore, given that the two set of data belonged to different years (2011 and 2012), a
scale parameter ($\lambda$) had to be included in the modelling, multiplying the indirect utility for the 2012 data. This allowed to account for any variance difference between sub-samples.

The results show that the goodness of fit improves when incorporating the habit factor, compared with the base situation (traditional model). It is worth mentioning that the waiting time coefficient is not different from cero, which could be due to the elevated frequency of public transport in the study area. Incorporating the habit factor makes this result even stronger.

It is worth mentioning that both the model with attitude and the model with habit had a similar fit and results, although they were estimated using different approaches: latent and non-latent variables. This finding reinforces some previous results that suggest that attitude is a good precursor of habit (or the opposite) [9]. In other words, there is a strong correlation between having a positive attitude towards a mode and the level of habit regarding its use.

5 Social assessment considering flexible demand models

Previous demand models were used to predict modal split once the intervention described in section 3 was in place. As mentioned before, the original CBA considered a fixed OD matrix, which was non-sensitive to the changes on travel times and costs. As a consequence, the CBA had to be redeveloped, using the data from the original study [20] but with changes in the OD matrices. This procedure was made using the traditional and advanced demand models. Level of service variables and cost were used to re-estimate the demand by transport mode, mimicking the equilibrium between supply and demand. Table 3 contains the outcome of the assessment, for the original evaluation and the new two models.

The results show that, when the assumption about a fixed OD matrix is relaxed, results change dramatically. Comparing the original evaluation with the one considering a traditional demand model, it is observed that the net present value (NPV) for the new scenario is almost three times the original one. Internal rate of return (IRR) and Rate of Return for the first year (RR1) are quite promising, being above the requested 8% for approval according to the Chilean norms. In addition, the Net Present Value for the first year (NPV1) is positive in spite of the massive level of investment: 22,080 millions of Chilean pesos (USD 40 million), which includes two bridges on a channel. Relaxing the assumption of a fixed OD matrix looks fine, but it seems that there is an overestimation of the benefits, due to changes on the modal split.

When considering the evaluation results for the case of using an advanced demand model which includes habit, results become more conservative since all indexes are smaller than the original ones. In fact, even though the NPV is roughly positive, the IRR is below the required 8% threshold. As a consequence, the outcome of the investment decision process would have been different compared to the original case.

Theoretically, it seems that the presence of habit, as a non-rational behavior, might affect the outcome of the decision making process regarding transport investments. Actually, many successfully assessed interventions using traditional demand models might lead to the wrong
results once built due to the no consideration of these factors rooted on users’ conduct. As shown in this work, the outcome might vary dramatically.

6 Comments and conclusions

The empirical case presented in this study adds evidence on that the decision making process is sensitive to the assumption made with respect to the changes on the demand levels. Assuming a constant demand, even when there are important changes on the level of service attributes, is a very strong and conservative decision.

Nevertheless, it is not enough to relax the previous assumption. Adopting flexible demand models, allowing for changes in modal split, for instance, might not look good either. A simple demand model might shift the balance on the other direction, suggesting that an intervention is quite superior using the standard evaluation indexes. Recognizing that changes on the level of service attributes affect the demand and the outcome of the assessment is not enough if the appropriate demand models are not used.

The incorporation of soft factors into the modal split model has proved that the outcome of a decision process may not be as positive as expected from a traditional demand model approach. Habit would be affecting, for instance, the decision of people regarding the expected conduct about shifting mode due to a transport intervention. If the demand models do not take fully into account these personality influences, and these models are used to support the decision making process, then we might come up with the wrong response to the existing or expected problem, with the associated opportunity cost for the public money.

We have assumed in this paper that there is a change on modal split due to the change in the level of service related to the exclusive bus lane. A further analysis should take into account that car users might adjust their decision about mode shifting after noticing that travel time is reduced due a lower congestion level. A new equilibrium between modes would be achieved if this adjust is carried out in an iterative fashion.

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REFERENCES


Figure 1: Incorporation of latent variables into a discrete choice model

- **Explanatory Variables** → **Latent Variables** → **Utility** → **Choice**
- **Latent Variables** → **Indicators**

- **Utility** is influenced by **Explanatory Variables** and has an error term **(ε)**.
- **Latent Variables** have an error term **(η)**.
- **Indicators** have an error term **(υ)**.

*Discrete choice model* and *Latent variable model*.
Figure 2: Case study area and location of the intervention

Figure 3: Design detail for alternative under study
Table 1: Socio-demographic information Collao respondents

<table>
<thead>
<tr>
<th>Household income (CLP*1,000)</th>
<th>Mode Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Car</td>
</tr>
<tr>
<td>0 - 400</td>
<td>4</td>
</tr>
<tr>
<td>400 - 1,000</td>
<td>30</td>
</tr>
<tr>
<td>&gt;1,000</td>
<td>51</td>
</tr>
<tr>
<td>Total</td>
<td>85</td>
</tr>
</tbody>
</table>

1 USD $≈$ 500 CLP (2013)

Table 2: Model results: Traditional and advanced (incorporating habit)

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Model</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Traditional</td>
<td>Advanced</td>
</tr>
<tr>
<td>$\theta_{\text{driver}}$</td>
<td>2.92 (6.2)</td>
<td>2.29 (5.0)</td>
<td></td>
</tr>
<tr>
<td>$\theta_{\text{bus}}$</td>
<td>4.19 (7.4)</td>
<td>5.23 (7.7)</td>
<td></td>
</tr>
<tr>
<td>$\theta_{\text{shared taxi}}$</td>
<td>2.67 (4.4)</td>
<td>3.76 (5.1)</td>
<td></td>
</tr>
<tr>
<td>$\theta_{\text{walking}}$</td>
<td>4.52 (6.7)</td>
<td>5.47 (7.1)</td>
<td></td>
</tr>
<tr>
<td>$\theta_{\text{cost/income}}$</td>
<td>-0.022 (-2.7)</td>
<td>-0.030 (-2.3)</td>
<td></td>
</tr>
<tr>
<td>$\theta_{\text{travel time}}$</td>
<td>-0.18 (-5.7)</td>
<td>-0.19 (-5.0)</td>
<td></td>
</tr>
<tr>
<td>$\theta_{\text{waiting time}}$</td>
<td>-0.06 (-1.9)</td>
<td>-0.03 (-0.7)</td>
<td></td>
</tr>
<tr>
<td>$\theta_{\text{access time}}$</td>
<td>-0.13 (-3.2)</td>
<td>-0.15 (-2.2)</td>
<td></td>
</tr>
<tr>
<td>$\theta_{\text{habit}}$</td>
<td>-</td>
<td>3.30 (5.1)</td>
<td></td>
</tr>
<tr>
<td>$\lambda_{\text{Collao 2012}}$</td>
<td>0.113 (7.5)</td>
<td>0.196 (6.7)</td>
<td></td>
</tr>
<tr>
<td>$\bar{p}$</td>
<td>0.123</td>
<td>0.200</td>
<td></td>
</tr>
<tr>
<td>LL</td>
<td>-214.2</td>
<td>-195.4</td>
<td></td>
</tr>
</tbody>
</table>

In parenthesis, t test compared with 0, with the exception of (*)

Table 3: CBA results, original and modified models (CLP*1,000,000)

<table>
<thead>
<tr>
<th>Index</th>
<th>Original study</th>
<th>Traditional demand model</th>
<th>Demand model with habit</th>
</tr>
</thead>
<tbody>
<tr>
<td>NPV</td>
<td>6,664</td>
<td>19,864</td>
<td>783</td>
</tr>
<tr>
<td>IRR</td>
<td>8.6%</td>
<td>13.3%</td>
<td>6.3%</td>
</tr>
<tr>
<td>RR1</td>
<td>4.16%</td>
<td>8.46%</td>
<td>2.76%</td>
</tr>
<tr>
<td>NPV1</td>
<td>-383</td>
<td>513</td>
<td>-676</td>
</tr>
</tbody>
</table>

1 USD $≈$ 500 CLP (2013)