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Are respondents aware of the process strategies used in decision-making? Modelling business location decisions using multiple stated process strategies

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TITLE: **Are respondents aware of the process strategies used in decision-making? Modelling business location decisions using multiple stated process strategies**

ABSTRACT: Discrete choice studies are increasingly used in urban planning to understand preferences and to make informed decisions based on its outcomes. Traditional discrete choice modelling approaches have evolved in a setting in which some very specific behavioural assumptions are made in specifying decision-making. These assumptions have given rise to the study of alternative process strategies in decision-making, such as majority of confirming dimensions (MCD), attribute non-attendance (ANA), or value learning (VL). In this paper, a stated choice experiment was designed to understand business location decisions, where a location specialist had to compare their current location with two alternative locations. After each choice task, respondents were asked whether they used ANA in processing the choice tasks, and at the end of the experiment a number of questions were asked to identify whether specific process heuristics were used such as MCD and VL. Choice models were estimated to compare the influence of including different stated heuristics responses. The results show that the model which included the stated heuristics responses is superior in terms of the goodness of fit and in the estimates' significance levels. The willingness to pay estimates derived from a traditional model were statistically equivalent to the ones derived from the stated multiple heuristics model. However, the median WTP derived from the stated multiple heuristics model was slightly higher and the confidence intervals lower than in the traditional model.

KEY WORDS: ***Business location decisions, process strategies, stated heuristics, discrete choice models, stated choice experiment***

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1. Introduction

Discrete choice studies are becoming more popular in urban planning investigations as a way to understand preferences and to make informed decisions based on its outcomes. Traditional discrete choice modelling approaches have evolved in a setting in which some very specific behavioural assumptions are made in specifying decision-making. The most typical approach assumes that individuals act *as if* they choose the alternative that has the maximum utility which takes into account all the alternatives and attributes exactly as presented (Luce, 1959). This approach can be referred to as a linear in parameters and additive in attributes (LPAA) utility function (which as an extension allows for attribute interaction). These assumptions have given rise to the study of alternative process strategies in decision-making, such as majority of confirming dimensions, attribute non-attendance, and value learning. Process strategies can be respondents whether they ignored certain attributes, referred to as stated attribute-non-attendance. However, there is a limited literature on the role that information identified through stated process strategy questions helps in explaining a discrete choice outcome. This paper asks questions to elicit the process strategies being used in decision-making, and whether accounting for these stated responses in estimation of choice models provides an improved understanding of preferences, in contrast to the inference approach.

The interest of this research is in understanding the decisions made by businesses on where to locate or relocate, which are typically given less consideration than residential location in integrated transport and land use modelling systems. This is surprising given the important role that businesses play in defining employment opportunities, and hence the travel patterns of workers and any travel associated with accessing firms. As part of a larger study on giving firm location choices an endogenous representation in an integrated model system, data has been collected with the purpose of understanding relocation decisions in the Greater Sydney Metropolitan Area, Australia.

A stated choice experiment is the centrepiece of the survey and included questions relating to the decision process strategies used by respondents. After each choice task, respondents were asked which attributes they attended to or not. At the completion of all choice tasks, respondents were asked a series of question designed to elicit the process strategies they adopted in choice making throughout the choice experiment. This study focuses on LPAA, value learning (VL) and the majority of confirming dimensions (MCD). The responses to all these process strategies will then be used in such a way that each respondents utility function will be specified dependent on their answers to the process strategies questions. To the best of our knowledge, this is the first study to use stated VL, LPAA and MCD responses jointly in the formulation of such utility functions. Stated ANA has been used previously in literature but, as far as we are aware, not in combination with the previous stated process strategies. The main contribution of this paper is to provide guidelines as to the potential value of using stated alternative process strategies and how they can be incorporated into the modelling of choices.

The following sections are structured as follows. Section 2 provides a brief background of the process strategies selected, and of stated or inferred heuristics. Section 3 presents the empirical setting and choice experiment, followed by a descriptive profile of respondents. Section 4 presents the methodology used, and the next sections present the results and willingness to pay estimates. The final section presents an overview of the main findings.

2. Background

This study focuses on the traditionally used LPAA approach and three others: attribute non-attendance (ANA), majority of confirming dimensions (MCD) and value learning (VL).

Attribute non-attendance (ANA)

Attribute non-attendance (ANA) proposes that individuals might not consider all the attributes that describe each alternative; that is, some of them might be ignored or not attended to. This alternative process strategy has been widely used as it has proven to have a significant influence on individuals' preferences (Hensher et al. Rose, & Greene, 2005; Hensher, 2006; Puckett & Hensher, 2009; Weller, Oehlmann, Mariel, & Meyerhoff, 2014; Collins & Hensher, 2015; Balbontin, Hensher, & Collins, 2017). ANA has been represented in choice models in two ways: stated ANA, where individuals are asked directly which attributes they did not attend to; and inferred ANA, where the attributes that are ignored are estimated in the model.

Hensher et al. (2005) were the first to recognise the role of ANA based on supplementary information provided by respondents at the end of a stated choice experiment. Their results show that including ANA has a statistically significant influence on the WTP estimates. Puckett & Hensher (2009) studied whether asking respondents to determine which attributes they did not attend to after each choice task or after the whole experiment influence the model parameter estimates. Their results showed that respondents do not always ignore the same attributes in every choice task; thus, it is preferable to ask them after each choice set (which can account for the attribute levels in each choice scenario).

Some studies have also looked into the differences between stated and inferred ANA. Hess & Hensher (2010) compared results using stated ANA and inferring it. Their results from the inferred ANA model are not always consistent with the stated ANA responses; and there is some evidence to suggest that individuals that say they ignored an attribute actually assigned it lesser importance. The results obtained from the inferred approach had a slightly better fit and more consistent results. Weller et al. (2014) compare inferred and stated responses and analysed the influence that the same design may have on the ANA heuristic. Their results show that a higher number of alternatives increased the probability of non-attendance, both for stated and inferred specifications. Specifically, they found that for stated non-attendance a higher number of levels for the cost attribute increased the probability of non-attending it; and for inferred non-attendance, a higher number of alternatives increased the probability of not-attending to the cost attribute. Collins & Hensher (2015) studied the influence of the experiment design on inferred attribute non-attendance using a latent class random parameter approach, which will be referred in this study as *Probabilistic Decision Process,* where each class represents a heuristic. They also confirmed the finding that when the number of attribute levels is larger, there seems to be more ANA, and some attributes are more likely to be not attended. Also, their findings suggest the WTP estimates significantly change when considering stated versus inferred ANA.

Majority of confirming dimensions (MCD)

The majority of confirming dimensions (MCD) heuristic considers that individuals assess each alternative through how many 'best' attribute levels exist. For each attribute, a respondent looks for the alternative that has the 'best' level and marks that one as the best performing attribute level. The alternative that has the larger number of best performing attribute levels is the chosen one. Russo & Dosher (1983) conducted a study where respondents were asked to determine the decision process strategy used. Their eye movements were recorded to compare these to the stated strategy used.

They propose the MCD heuristic as a form of reducing the processing effort required by the choice task. Thus, instead of comparing the attribute level values, they assign a value -1 to +1 to the 'worst' and 'best' performing attribute level. Russo & Dosher (1983)'s results showed that this criterion was not always correct, and almost half of the times it was wrong, which could be suggesting process heterogeneity. They mention that this could have been caused by small differences among the attribute levels.

Hensher & Collins (2011) include this heuristic by identifying the number of best performing attribute levels as an additional variable in the utility function. The estimated parameter for this component was highly significant and positive, suggesting that when the number of best performing attribute levels is higher, the probability of that alternative being chosen increases. Hensher & Collins (2011) asked respondents to state which attributes they did not attend to. These responses enabled them to test the majority of confirming dimensions heuristic using only the attributes that were attended to, which improved the model performance even more. In their conclusions, the authors recommend further inquiry into underlying sources of process heterogeneity directly in the utility expressions that represent individual preferences. A similar method will be used in this research to include the MCD heuristic.

Value learning (VL)

This heuristic represents a situation where the principle of preference stability is violated, and assumes that throughout the experiment, individuals discover their preferences. This heuristic underlies a theory that individuals have weak preferences, which can be influenced by the alternatives shown to them. This was originally proposed by Plott (1996) as a discovery preference hypothesis that argues that stable and theoretically consistent preferences are formed by practice and repetition. This was later analysed in a discrete choice experiment context by Bateman, Burgess, Hutchinson, & Matthews (2006); Bateman et al. (2008); Hensher & Collins (2011); McNair, Hensher, & Bennett (2012); Balbontin et al., (2017) and Balbontin, Hensher, & Collins (2019).

Balbontin et al., (2017) and Balbontin, Hensher, & Collins (2019) propose a value learning definition that states that the 'best' performing attribute levels of the chosen alternatives throughout the experiment have an influence on the assessment of the current choice task. Their results show that including this definition significantly improves the results. An equivalent definition of VL will be used in this study.

3. The Empirical Setting and Choice Experiment

The first step to design the choice experiment was to understand business location decisions in the Greater Sydney Metropolitan Area (GSMA). For this, a literature review was carried out to define a list of attributes that have shown to have an influence on business location decisions, such as public transport and/or accessibility indicators, rental price, density, parking, number of employees in the area, tax burden, agglomeration (Gabe & Bell, 2004; Elgar et al., 2009; Kimelberg & Williams, 2013; Weterings & Knoben, 2013; Hensher, Teye, et al., 2017; Jiang et al., 2018; Balbontin & Hensher, 2019). Afterwards, extensive in-depth interviews were carried out with key business location decisionmakers in Sydney, who were extremely useful in providing insight on the GSMA context and selecting the eight most relevant attributes, which will be described below[1].

We designed an online survey which consisted of four parts. The first part asked questions about a firm's current location characteristics, their business profile (including clients and competitors), and the respondents' profile. Subsequently, a series of attitudinal questions were asked regarding physical infrastructure, economic infrastructure and quality of life. The third part was an efficient stated choice experiment, and the final part asked about the process strategies used during the choice experiment.

One of the most important issues in a business location choice experiment is identifying the right people to answer the survey. That is, people that are involved in the location decisions of their company or work as advisers in business location decisions. A panel survey company was hired who contacted businesses directly and searched for workers involved in business location decisions. We made sure to clarify in the invitation that we were only interested in businesses located within the GSMA and that the respondent was involved in an organisations business location decisions. Additionally, we included two questions at the beginning of the survey to screen out those respondents who were geographically out of the scope or not involved in their business location decisions.

In the choice experiment, three alternatives were presented: the current location and two alternative locations. These were described using eight attributes associated with accessibility, office and business profile (Table 1) Accessibility was described using public transport service frequency, walking time to the closest rail station, client accessibility, and distance from your current business location. The office/business profile was described by the following attributes: rental space cost, amount of office space, lease commitment and agglomeration (i.e., number of businesses offering the same or similar products and/or services in the local area[2]).

Table 1: Attribute levels description in the stated choice experiment

CATEGORY	ATTRIBUTES	LEVELS (5)	PIVOT/RULE	EXPECTED SIGN
ACCESSIBILITY	Public transport service frequency in peak to anywhere (minutes)	Every 5, 10, 15, 30, 60	Not pivoted	-
	Walking time to the closest rail station (minutes)	5, 10, 15, 25, 45	Not pivoted	-
	50% of your clients are accessible within (minutes)	-50%, -25%, 0%, 25%, 50%	Pivoted	-
	Distance from your current business location (kilometres)	2, 7, 15, 30, 50	Not pivoted	?
OFFICE PROFILE	Rental space cost (annual AUD$ per square metre)	*If current < AUD$500:* -50%, -25%, 0%, 25%, 50% *Otherwise:* -50%, -25%, 0%, 12.5%, 25%	Pivoted	-
	Amount of office space (square metres)	-50%, -25%, 0%, 25%, 50%	Pivoted	?
	Lease commitment (years)	3, 5,10,15,20 years	Not pivoted	-
LOCATION PROFILE	Number of businesses offering the same or similar products and/or services in the local area[1]	-75%, -50%, 0%, 50%, 75%	Pivoted	?

[1] For more information on the interviews and literature review, the reader is referred to Balbontin & Hensher (2019).

[2] The term local area is defined as a catchment area that is 5 kms in radius around their current business location (where the business operates).

Respondents were asked to choose their preferred alternative. If they chose their current location as their preferred alternative in a specific choice task, respondents were asked to additionally choose one other alternative assuming their current location was no longer available. Each respondent was faced with four different choice tasks and depending on how many times they chose their current location in each of these, we obtained between 4 and 8 choices. A choice task example is presented in Figure 1.

Features	Current location	Location 1	Location 2
Public transport service frequency in peak to anywhere	15 mins	30 mins	15 mins
Walking time to the closest rail station	10 mins	45 mins	25 mins
50% of your clients are accessible within	50 mins	63 mins	50 mins
Rental space cost ($ per square metre)	$100	$50	$150
Amount of office space (square metres)	100㎡	125㎡	50㎡
Lease commitment (years)	5	5	15
Number of businesses offering the same or similar products and/or services in the local area	11-20	8	15
Distance from your current business location	-	15 kms	7 kms
Q1. Which alternative would be **most attractive (i.e. preferred)** as a business location?	◉	○	○
Q2. If your current location was not available anymore, which alternative would you select?		○	○

Figure 1: Example of a choice task

After each choice task, individuals were asked to select which attributes they ignored when making a decision. At the completion of the business location stated choice experiment, we included some questions to help in understanding how they had made their choices in the previous choice sets; that is the process rules that are used to arrive at a choice response. The questions were formulated from a pilot investigation, using the feedback from individuals who are not familiar with choice modelling, to assist in ensuring that the sample understands the meaning of each response option. The questions associated with process rule revelation are the following:

1. *Did the characteristics of the alternatives provided in the earlier choice tasks influence your decisions in the subsequent choice tasks? Yes or No*
2. *What made you choose one alternative? (Please select all that apply)*
    a. *I chose the **first** alternative whose characteristics satisfied my requirements (ignoring the remaining alternatives).*
    b. *I eliminated alternatives that failed to meet my requirements, starting with the most important characteristics.*
    c. *I compared the alternatives' characteristics considering that some characteristics are more important to me than others*
    d. *I chose the alternative that has the highest number of best performing characteristics (relative to the other alternatives).*
    e. *Others. Please specify.*

In this paper, the focus is on four different process strategies: (1) Attribute non-attendance; (2) Value learning (VL); (3) Majority of confirming dimensions (MCD); and (4) Traditional linear in the parameters and additive in the attributes (LPAA). The first question presented above determines if the individual used value learning, which states that individuals discover their preferences throughout the experiment. The second question considers different heuristics and whether individuals choose more than one processing rule. We focus on the answers to questions 2c and 2d, where the first one represents the standard fully compensatory form (linear in parameters and additive in attributes (LPAA)), and the second one MCD. As can be seen, there was no limitation on how many process strategies were being used, as an individual might use more than one heuristic simultaneously, something that is testable in model estimation.

4. Descriptive Profile of Respondents

203 businesses participated in the survey providing a total of 1,333 observations from the stated choice experiment. Some of these responses were detected as data errors or outliers for two main reasons:

1) They do not own the building where they are located, and their rental space cost is lower than $30. This is considered too low given the average in Sydney that varies between $100 to $120 per square metre per annum (net plus GST) (Herron Todd White, 2017).
2) Their office space square metres per employee was lower than 5. In Australia, the legal minimum is 10 square metres per employee. Given that some businesses might have employees working from outside the office, we considered the acceptable limit to be 5 square metres per employee.

A total of 44 businesses were excluded, resulting in a final data size for model estimation of 1,051 observations. A summary of the main variables used in this study are summarised in Table 2.

Table 2: Summary of the attributes' levels and process strategies used in the sample

Alternative's characteristics	**Mean (std dev)**	**ANA**
Public transport frequency (hours)	0.40 (0.38)	29%
Walking time to closest rail station (hours)	0.35 (0.33)	29%
Client accessibility (hours)	1.17 (1.54)	28%
Rental space cost (AUD$'00 per square metre per annum)	3.97 (4.06)	14%
Amount of office space ('00 square metres)	10.94 (20.27)	9%
Lease commitment ('0 years)	1.02 (0.69)	20%
Agglomeration ('0 number of businesses)	1.51 (1.88)	41%
Distance to current location (kilometres)	15.69 (17.52)	19%
Process strategies	***%***	
Did the characteristics of the alternatives provided in the earlier choice tasks influence your decisions in the subsequent choice tasks? Yes	44%	
What made you choose one alternative?		
I chose the first alternative whose characteristics satisfied my requirements (ignoring the remaining alternatives).	25%	
I eliminated alternatives that failed to meet my requirements, starting with the most important characteristics.	28%	
I compared the alternatives' characteristics considering that some characteristics are more important to me than others	28%	
I chose the alternative that has the highest number of best performing characteristics (relative to the other alternatives).	17%	
Others. Please specify.	2%	

The majority of empirical studies in the literature that investigate the role of process heuristics typically assume that each respondent uses one process strategy in decision-making. Exceptions include Balbontin, Hensher, & Collins (2017b), Hensher, Balbontin, & Collins (2018) and Balbontin et al. (2019). When asking individuals to answer which process strategies they used in the previous choice task questions, many of them indicated through their response that they were using more than one. Table 3 presents these results, where it shows that 32% did not use LPAA, MCD or VL; 19% used only VL; 13% used only LPAA; 14% used both LPAA and VL; 7% used both MCD and VL; and 3% of the sample used the three rules. ANA is considered separately as it was asked for each choice task, whereas MCD, LPAA and VL where asked at the end of the choice experiment. ANA results specific to each attribute are presented in the last column of Table 2, where agglomeration is the attribute which was more frequently ignored, and the amount of office space the less frequently ignored. For the whole sample, 84% of individuals ignored an attribute in at least one choice task.

Table 3: Combination of VL, MCD and LPAA process strategies being used in the sample

Combination of process strategies	Number of observations	%
LPAA + MCD + VL	32	3%
LPAA + MCD only	54	5%
LPAA + VL only	150	14%
MCD + VL only	75	7%
Only LPAA	137	13%
Only MCD	62	6%
Only VL	201	19%
None	340	32%

The use of MCD can be tested directly without the need to estimate a choice model. Those respondents that said they had MCD are expected to have chosen the alternative that had the highest number of best performing attributes presented in the stated choice experiment. Table 4 presents the percentage of respondents that chose the alternative with the highest number of best performing attributes for the total sample and for those who said they used MCD. The table also summarises the results with and without ANA: with ANA only counting the best performing attributes that were attended to. For the total sample, the contribution of ANA increases the percentage of respondents who use MCD from 61% to 71%. For the sub-sample who said they used the MCD rule, the results with and without ANA are similar, although slightly higher when allowing for ANA. These results show that 70% of the sample who indicated that they used the MCD processing rule actually chose the alternative with the highest number of best performing attributes, considering all the attributes (i.e., including those they said they ignored), and 68% considered only the attributes they said they attended to.

Table 4: Summary of MCD process strategy verification

% of individuals who chose the alternative with the highest number of best performing characteristics	
Total sample, without ANA	61%
Total sample, with ANA	71%
Respondents who said they used MCD, without ANA	70%
Respondents who said they used MCD, with ANA	68%

Two scores were calculated for each alternative, which represent the number of best performing characteristics with and without considering stated ANA. These scores will be included in the utility functions as will be shown in the following section.

5. Methodology

The purpose of this study is to analyse if individuals are aware of the process strategies they are using in decision-making, and if incorporating this information provides a better understanding of individual preferences. To do so, five choice models are estimated:

1) LPAA without ANA, where it is assumed every individual uses LPAA.
2) LPAA, where it is assumed every individual uses LPAA considering those attributes that are not ignored (ANA).
3) Stated multiple heuristics, where it is assumed that individuals use the heuristics they said they used.
4) Forced multiple heuristics, where it is assumed that everyone uses all heuristics regardless of what they said.
5) Probabilistic decision process (PDP), which is a latent class structure model where each class represents a different heuristic.

Models M1 and M2: LPAA with and without ANA

The LPAA model with and without ANA will both be estimated as mixed multinomial logit models with error components. Equation (1) shows the functional form of the utility function, where ASC_i is the alternative specific constant of alternative *i*; β_m is the parameter estimate associated with attribute *m*; $x_{m,i}$ is the level of attribute *m* for alternative *i*; η_{iq} is a component of the error term that varies across individuals but is the same within an individual *q*; and ε_i is the random error term.

$$U_i^{\text{LPAA model}} = ASC_i + \beta_1 \cdot x_{1,i} + ... + \beta_m \cdot x_{m,i} + ... + \eta_{iq} + \varepsilon_i \tag{1}$$

The model with ANA will only include the attributes *m* that each individual attended to in the utility function, and the model without ANA will include all of them regardless of individuals' stated ANA responses.

Model M3: Stated multiple heuristics

The stated multiple heuristics model first considers that individuals use those heuristics that they said they used. Initially, we included LPAA only for those individuals that had selected the affirmation "*I compared the alternatives' characteristics considering that some characteristics are more important to me than others*". However, results suggested that LPAA was statistically significant for all individuals, so the functional form for this model was specified as follows:

$$U_i^{\text{Stated heuristics model}} = ASC_i + LPAA_i + \delta_{Use\_VL} \cdot VL_i + \delta_{Use\_MCD} \cdot MCD_i + \eta_{iq} + \varepsilon_i \tag{2}$$

where δ_{Use_VL} represents a dummy variable which is equal to 1 if the individual answered that the attributes of the alternatives provided in the earlier choice tasks influenced their decisions in the subsequent choice tasks, and 0 otherwise; and δ_{Use_MCD} is a dummy variable equal to 1 if the individual answered that they chose the alternative that has the highest number of best performing attributes (relative to the other alternatives), and 0 otherwise. The utility function for each heuristic is defined as follows:

$$LPAA_i = \beta_1 \cdot x_{1,i} + \ldots + \beta_m \cdot x_{m,i} \tag{3}$$

$$VL_i = \beta_{VL} \cdot \left(\beta_1 \cdot x_{1,REF} + \ldots + \beta_m \cdot x_{m,REF} \right) \tag{4}$$

$$MCD_i = \beta_{MCD} \cdot MCDscore_i \tag{5}$$

β_{VL} and β_{MCD} represents the parameter estimates associated with the heuristics value learning and majority of confirming dimensions, respectively; $x_{m,REF}$ represents the 'best'[3] level of attribute *m* the individual has seen throughout the experiment in their chosen alternatives; and $MCDscore_i$ represents the number of best performing attributes of alternative *i* (relative to the other alternatives). This latter score represents the score only for the attributes that the individual attended to. The score without ANA was tested but was found to be superior in terms of goodness of fit. The VL definition in equation (4) only includes the reference component, defined as the 'best' attribute levels offered in the experiment. This was the most appropriate functional form given that this type of model considers that all respondents use the LPAA approach, and hence the contribution of VL in the utility function represents the value learning part only and does not repeating what the individual is observing in the current choice task which is included as part of LPAA.

Model M4: Forced multiple heuristics model

The forced multiple heuristics model is equivalent to the stated one, but it considers that every individual uses both of the VL and MCD heuristics. The utility function for this model is as follows:

$$U_i^{\text{Forced heuristics model}} = ASC_i + LPAA_i + VL_i + MCD_i + \eta_{iq} + \varepsilon_i \tag{6}$$

Model M5: Probabilistic decision process model

The probabilistic decision process model has a latent class structure where each 'class' represents a heuristic, and hence is different to the previous model behavioural response forms. Specifically, the definition of VL here is different as it will take into account what individuals have seen in the previous choice tasks, and what they are seeing in the current choice task. A *logsum* transformation was used in the VL class because the model results were superior in terms of the goodness of fit. The utility functions for the three different heuristics (or classes) are as follows:

$$Class\_LPAA_i = ASC_{i,LPAA} + \beta_1 \cdot x_{1,i} + \ldots + \beta_m \cdot x_{m,i} \tag{7}$$

$$Class\_VL_i = ASC_{i,VL} + \beta_{VL} \cdot \begin{bmatrix} \ln\left(1 + \exp\left(\beta_1 \cdot x_{1,i} - \beta_1 \cdot x_{1,REF}\right)\right) + \ldots \\ + \ln\left(1 + \exp\left(\beta_m \cdot x_{m,i} - \beta_m \cdot x_{m,REF}\right)\right) \end{bmatrix} \tag{8}$$

$$Class\_MCD_i = ASC_{i,MCD} + \beta_{MCD} \cdot MCDscore_i \tag{9}$$

[3] The worse and mean attribute levels seen in previous choice tasks were also tested. Even though the results were not statistically different, the 'best' specification was slightly better in terms of the model's goodness of fit.

It is important to note that the nature of the first question in each choice task (with the current location alternative present) is different to the second one, where individuals are asked to choose between the two alternative locations. Therefore, a scaling factor was included to take into account the differences between the choice task questions in all the models presented above. The results show that the scaling factor was not statistically significant at a 95% confidence level in any of the models.

6. Results

The results for the five models are presented in Table 5. We begin by comparing the LPAA model with and without ANA. The results show that including ANA significantly improves the goodness of fit of the model (log-likelihood and AIC/n) and suggests a significant impact on the *rent* attribute under ANA which is not statistically different from zero in the model without ANA. It was expected, *a priori*, that rent is an important location decision attribute, although it is reasonable that some businesses did not attend to that attribute because, for example, they own the building in which they operate and would plan to do the same if they moved location (although deemed rent as a tax deduction clearly applies). Therefore, the results presented show the importance of including stated ANA, with all subsequent allowing for ANA.

Informative evidence is revealed when comparing the stated and forced multiple heuristics. Even though the forced multiple heuristics model is superior in terms of goodness of fit (log-likelihood and AIC/n), several parameter estimates are not statistically significant at a 90% confidence level such as public transport frequency, rental space cost, lease commitment, and the VL heuristic parameter estimate. This finding suggests that when forcing everyone to use VL and MCD, there is a statistically significant effect on the parameter estimates and the significance level of otherwise important attributes. The stated multiple heuristics model seems appropriate in terms of the significance levels, which are all statistically significant with a 90% confidence level. 'Forcing' every individual to use all heuristics provides an improved overall goodness of fit; however, it impacts in a behaviourally worrying way on the interpretation of the findings; for example, that the rental space cost is not significant when deciding where to locate a business.

The PDP model can be compared to the LPAA or multiple heuristics models, and it can be seen that it has a worse overall goodness of fit. When including the dummy variables in the probability to choose each heuristic (i.e., to belong to each class), none of them were statistically significant. That is, people that said they chose VL were not more likely to belong to that heuristic/class than those ones that did not. This result also reflects the fact that the PDP approach assumes each individual is assigned to one class, that is, each individual uses only one process strategy. In our choice experiment, we allowed more flexibility in terms of the process strategies used, and the results suggest that individuals used more than one process strategy. This might be one of the reasons why this model was inferior in terms of goodness of fit, as it is more restrictive than the other definitions.

Given the significance level of the parameter estimates and the goodness of fit of the five models presented, the two preferred models are the stated multiple heuristics model and the LPAA model (with ANA).

Table 5: Stated and inferred models' estimates (t-values in parenthesis)

Parameters	Acronym	Alternatives	M1: LPAA without ANA	M2: LPAA	M3: Stated multiple heuristics	M4: Forced multiple heuristics	M5: PDP Class 1: LPAA	Class 2: VL	Class 3: MCD
ASC alternative locations - *mean*	ASC_ALT	Alternative locations	-	-	-	-	-	-	-
- *std dev*			2.610 (7.97)	2.560 (7.90)	2.450 (7.70)	2.380 (7.53)	-	-	-
ASC current location	ASC_CURR	Current location	1.080 (3.80)	1.050 (3.89)	1.110 (4.22)	1.180 (4.58)	1.970 (7.39)	2.820 (3.23)	-2.440 (2.39)
Public transport frequency	FREQ	All	-0.847 (4.24)	-1.560 (6.19)	-1.480 (5.84)	-1.030 (3.95)			-1.640 (5.34)
Walking time to closest rail station	WLKTR	Alternative locations	-0.910 (3.94)	-1.200 (4.34)	-1.090 (3.91)	-0.339 (1.07)			-1.270 (3.96)
Client accessibility	ACCESS	All	-	-	-	-			-
Rental space cost	RENT	All	-0.033 (0.71)	-0.107 (2.05)	-0.094 (1.80)	-0.003 (0.06)			-0.124 (2.09)
Amount of office space	SPACE	All	0.037 (3.90)	0.036 (3.64)	0.034 (3.50)	0.017 (1.82)			0.045 (4.15)
Lease commitment	LEASE	All	-0.259 (2.77)	-0.331 (3.22)	-0.293 (2.83)	-0.017 (0.14)			-0.234 (2.10)
Agglomeration	AGGLOM	All	-0.184 (4.01)	-0.264 (3.70)	-0.251 (3.53)	-0.182 (2.63)			-0.350 (3.58)
Distance to current location	DIST	Alternative locations	-0.024 (6.59)	-0.028 (7.30)	-0.029 (7.39)	-0.023 (5.63)			-0.029 (5.75)
VL heuristic	VL	All	-	-	-1.750 (1.76)	-1.610 (1.56)	-	3.030 (4.40)	-
MCD heuristic	MCD	All	-	-	0.194 (2.36)	0.305 (6.12)	-	-	0.391 (3.76)
Number of Parameters Estimated			9.00	9.00	11.00	11.00			17.00
Log Likelihood at convergence			-710.99	-693.34	-688.37	-669.49			-686.89
Log likelihood at zero			-986.37	-986.37	-986.37	-986.37			-986.37
AIC/n			0.152	0.148	0.148	0.144			0.149
Number of observations						1,051			

7. Willingness to pay estimates

The willingness to pay (WTP) estimates are important behavioural outputs in choice studies. Table 6 summarises the median WTP estimates for the two preferred models together with their confidence intervals. These were estimated using PythonBiogeme (Bierlaire, 2016), which allows us to use simulation to run a sensitivity analysis taking into account the variance covariance matrix[4]. With the WTP and the 5% and 95% quantiles, we will be able to analyse the differences between the models. The cost attribute used to obtain WTP median estimates in dollars is the rental price per square metre.

Table 6: Median willingness to pay estimates (AUD$) with confidence intervals

How much a respondent in willing to pay (AUD$) for a	**M2: LPAA model**			**M3: Stated multiple heuristics model**		
	Median	Confidence intervals		**Median**	Confidence intervals	
Decrease in public transport headway by 1 minute	**$22.39**	$13.71	$122.67	**$25.27**	$11.93	$78.00
Decrease in the walking time to the closest rail station by 1 minute	**$18.41**	$9.00	$82.33	**$20.04**	$7.43	$70.28
Increase in the amount of office space by 1 square metres	**$33.08**	$8.82	$155.86	**$36.09**	$12.01	$144.72
Decrease in the lease commitment by 1 year	**$28.10**	$10.07	$203.25	**$31.10**	$7.60	$119.04
Decrease in agglomeration by 1 business around their local area	**$22.96**	$8.07	$128.02	**$28.91**	$5.25	$96.81
Decrease in the distance to the current location by 1 km	**$25.26**	$13.95	$143.84	**$31.73**	$14.80	$89.87

A graphical representation of the median WTP estimates is presented in Figure 2, which shows an overlap in all the WTP estimates between the two models. These shows that the WTP estimates are not statistically different from each other when considering LPAA only (under ANA) or when considering the stated multiple heuristics model. However, it is interesting to note that for all the estimates the median WTP is always slightly higher and the confidence intervals are lower in the stated multiple heuristics model than in the LPAA. This is an important finding which suggests that part of the variation in the median WTP estimates can be explained by different process strategies being used – where these are directly asked to respondents and included in the models.

In terms of the accessibility variables, the results show that business would be willing, at the median level, to pay an additional annual rental price per square metre varying between $18.41 and $25.27 for improved public transport.

Businesses are also willing to pay an increase their annual median rental price by $25.26 in the M2 model or $31.73 in the M3 model per square metre in return for decreasing the distance to their current location by 1 kilometre. Businesses are also willing to pay a median value of $22.96 in the M2 model or $28.91 in the M3 model in order to reduce by 1 the number of businesses that offer similar products or services than they do in their local area (defined within a 5km radius). Although there are no statistically significant differences between the two models, when considering the confidence

[4] The reader is referred to (Bierlaire, 2017) for more information on the sensitivity analysis. We used 500 draws for the sensitivity analysis simulations.

levels, the median WTPs are different enough to have a significant influence if they are used when assessing a new public transport project.

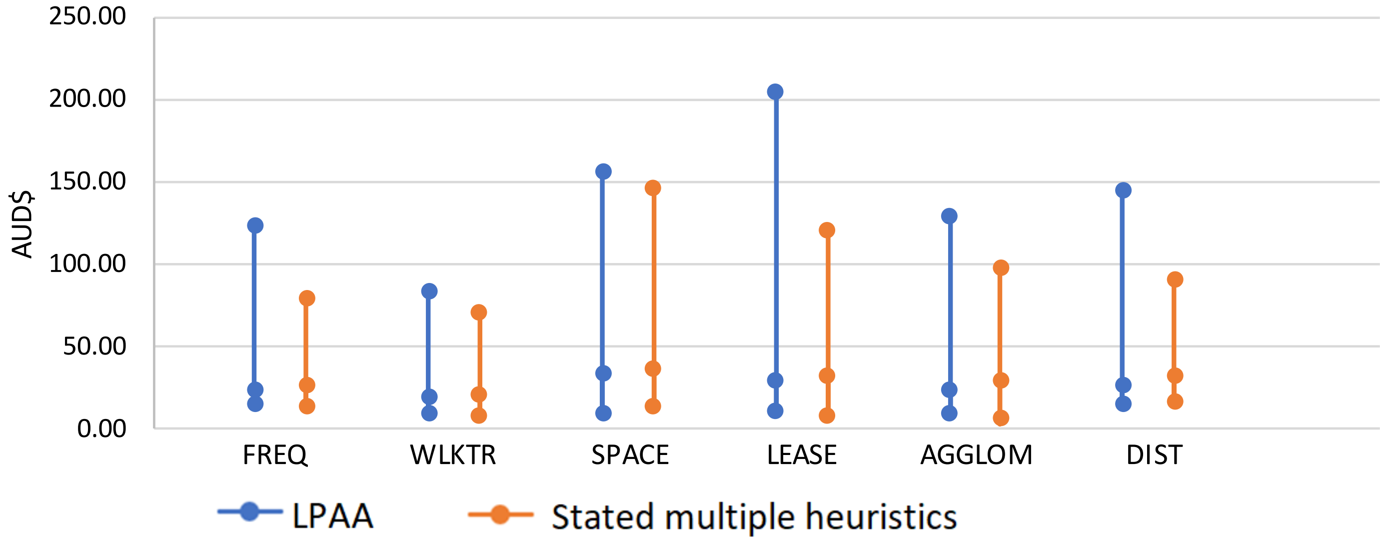

Figure 2: Median willingness to pay estimates (AUD$) with confidence intervals

8. Conclusion

This paper investigates the behavioural and welfare implications of incorporating multiple process strategies in choice models through the inclusion of additional information provided by respondents on how they processed the choice tasks shown to them in the stated choice experiment. Questions were asked to respondents to determine if they had used a traditional LPAA, an MCD heuristic and/or a VL heuristic throughout the experiment, and if they had ignored certain attributes (ANA) in each choice task. The results showed that ANA was statistically significant when eliciting preferences, suggesting that individuals are aware of the attributes they are ignoring. ANA was subsequently included as part of the integration of the other three process heuristics.

To incorporate LPAA, MCD and VL, three different functional forms were specified: M3) Stated multiple heuristics model, where each individual uses those heuristics he/she said they had used; M4) Forced multiple heuristics model, where every individual uses LPAA, MCD and VL together (plus ANA which is considered in each heuristic), and; M5) Probabilistic Decision Process (PDP), where each individual can use each heuristic up to a certain probability. M5 is the only one of these three models that allows each individual to use only one heuristic, and the results show an inferior goodness of fit given the number of parameters estimated relative to the other two models. This supports the hypothesis that individuals might be using more than heuristic at the same time, which was allowed for when asking for the process strategies used in the choice experiment. The goodness of fit of the M4 model was statistically superior to the M3 model; however, the M4 parameter estimates are behaviourally inconsistent to what was *a priori* expected (for example, that the rental price is relevant when choosing where to relocate). This finding suggests that imposing a condition in modelling that everyone uses all the process strategies is likely to bias the parameter estimates in such a way, that some of them become statistically insignificant whereas in reality, as shown through the other models, they are statistically significant. The results were compared to a traditional LPAA model (M2) where all the parameter estimates were significant, and together with the M3 model, were chosen as the preferred behavioural representation of choice.

In this research, we asked specific questions to identify which process strategies each individual had used in responding to each choice task. Interestingly, individuals that said they had used what we defined as the LPAA heuristic did not have a different behaviour than the ones that said they had not used it. That is, when including the stated LPAA responses as part of the utility function, the model had an inferior goodness of fit than when not including it. This might be due to the way in which the question was phrased or that the utility function of a LPAA approach is indeed an appropriate representation of different strategies that individuals might be using. If stated process strategies are being used, the phrasing of the questions is very sensitive, and it is important to make sure they can be understood by everyone in a similar way. Analysing the effect of different ways to ask about the same heuristic would be an interesting addition to the literature in stated process strategies, as well as the study of other process heuristics.

The WTP estimates derived from the LPAA model (M2) were statistically equivalent to the ones derived from the Stated multiple heuristics model (M3). However, the median WTP for all the attributes was slightly higher in the M3 model and the confidence intervals were lower than in the M2 model. This suggests that even though there are no statistically significant differences between the two models, there are certain patterns that reveal an important influence associated with including stated alternative process strategies. This paper presents interesting findings that suggest that asking respondents for additional information on the process strategies used and including these responses in the models, provides a way of building our understanding of decision-making in the context of business location decisions. The results provide new insights that can be used in cost-benefit analyses when assessing transport projects, which traditionally do not consider business location impacts. Our results show that accessibility has a significant impact in business location decisions which suggests that they should be considered when looking at the wider economic impacts of new projects.

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