Conference paper

Consumers' preferences for different energy mixes in Australia

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Highlights

- Overall, residents of Australia are willing to pay more for a cleaner energy mix.
- Heterogeneous preferences and WTP for energy sources occur across states.
- Biomass (nuclear) is the (least) preferred source across all states.
- A dissonance emerges looking at national and state level preferences.

Abstract

Policy makers worldwide face several challenges in addressing climate change, including an understanding of how to successfully introduce initiatives reliant on renewable energy sources (RES). A key component in this is understanding citizen preferences in terms of willingness to pay (WTP). This research focuses on utilising a discrete choice experiment and associated hybrid choice model to model individual WTP for four different RES types (biomass, hydro, solar and wind) against four current and potential non-RES types (gas, oil, nuclear and coal). The model accounts for latent segments in relation to WTP based on pro-environmental attitudes and various socio-demographics. The research examines the case of Australia, but reports on WTP at each state and territory level rather than at the national level. The findings indicate that respondents from different states and territories have heterogeneous preferences in terms of energy mix composition, which led to different WTP values. A large dissonance emerges also comparing preferences at national and state/territory level, which may potentially act as hindrance to the achievement of the goal set for the Paris agreement.

Keywords: energy mix; willingness to pay; preference; discrete choice experiment; hybrid choice model;

1. Introduction

One of the biggest threats to the contemporary age is undoubtedly climate change. As reported during the Intergovernmental Panel on Climate Change, "it is extremely likely that human influence has been the dominant cause of the observed warming since the mid-20th century" (IPCC, 2013). To address this phenomenon, 196 parties have since signed the Paris Agreement according to which they committed to keep a global temperature rise this century well below two degrees Celsius above pre-industrial levels. Under the assumption that climate change is mainly caused by the human induced emission of greenhouse gases, an outcome in reaching this target is to increase the share of renewable energy sources (RES) in the energy mix composition.

Policy makers worldwide face the challenge of replacing fossil fuel with green sources in order to contribute to a friendlier environment and to limit natural catastrophes. To inform policy development, it is important to understand citizens' preferences and willingness to pay (WTP) for different energy sources. For example, a positive WTP for a particular renewable source signals a consumer surplus and suggests a potential levy that could be introduced to support the costs for developing the infrastructure necessary to generate energy from that specific source. Willingness to pay represents therefore one of the most important inputs for policy makers.

In the literature on energy, WTP is usually derived by means of either Contingent Valuation (CV) or Choice Experiment (CE) methods. CV employs a direct question to elicit the respondents' WTP. For example, Zorić and Hrovatin (2012) used an open-ended CV question asking those agreeing to partake in a green electricity scheme in Slovenia to nominate how much extra they would be willing to pay per month on their existing electricity bills in order to participate. CE instead are based on the choice amongst competing (non-trivial) alternatives defined in terms of attributes and levels, which can be used to *indirectly* calculate a WTP measure if one or more of the attributes represents some form of cost. In the past two decades, CE is becoming increasingly popular at the expense of CV methods for two main reasons. First, through CEs, it is possible to estimate the marginal WTP, and second, the marginal WTP can be calculated for all the attributes contained within the experiment, providing more information to policy makers. Most studies in the literature on energy using CEs elicit the WTP of respondents for the aggregate set of renewable energy sources. However, estimating such a value for the aggregate set of RES rather than for specific sources (i.e., wind, hydro, solar) limits the information that can be provided to policy makers. Indeed, prior literature indicates that consumers' WTP varies across electricity generated from different sources, producing different consumer surpluses.

An in-depth examination of this literature reveals that most research employing the CE technique to calculate WTP for separate sources have been conducted either in America or in Europe. In the US, this includes studies by Goett et al. (2000), Borchers et al. (2007), Komarek et al. (2011) and, more recently, Yoo and Ready (2014). Aravena et al. (2012) undertook their study in Chile. In Europe, similar studies have been conducted in Scotland (Bergmann et al., 2006), Italy (Cicia et al., 2012), Germany (Kaenzig et al., 2013), Finland (Kosenius and Ollikainen, 2013), Denmark (Yang et al. 2016) and Norway (Navrud and Braten, 2007). Meta-analysis has also been undertaken by Ma et al. (2015) and Sundt and Rehdanz (2015), both of which include studies using both CE and CV methods in their analysis to provide information on WTP for specific sources.

One country that emits a considerable amount of greenhouse gases (GHG) per capita is Australia, listed as 8th and 13th in the world in 2013 and 2017 respectively (World Resources Institute, 2017). Nevertheless, few studies have explored the Australian citizens' preferences and WTP for renewable energy sources. Using CV, Ivanova (2013) estimated the WTP of three classes of citizens of Queensland, namely *Concerned, Protest* and *Willing to Pay* classes, for an increase of the share of RES in the energy mix; the study did not distinguish the WTP amounts for specific energy sources however. Ma and Burton (2016) explored the consumers' choice of green products and their commitment levels on a sample of residents in Perth, the capital city of Western Australia. Although the design of the CE includes separate sources of energy (solar, wind and hydro), the authors do not provide explicit WTP values, they did demonstrate support for solar energy, whilst hydro and wind do not have any impact on the consumers' choice. To the best of our knowledge, the only research that employs data collected across the entire country is by Tranter (2011) who examined political divisions over climate change and environmental issues in Australia. The author finds that labour and green supporters are willing to pay more than liberal supporters for energy generated by renewable energy sources. Again, the WTP for specific energy sources is not reported.

The objective of this research is to provide a national mapping of Australian citizens' preferences for the different energy sources taking into account their place of residence, socio-demographic characteristics as well as inclination towards the environment. An on-line CE was distributed across the eight Australian states/territories (New South Wales, Queensland, Victoria, South Australia, Tasmania, Western Australia, Australian Capital Territory and Northern Territory). The design of the experiment allowed the exploration of residents' WTP for different energy sources, both renewable and non-renewable, and considers that WTP may be heterogeneous across Australian citizens. Understanding the preferences (for the different energy sources) of the residents of the different states and territories is crucial for meeting the goals of the Paris Agreement. Since Australian states and territories can decide the energy mix composition in almost total autonomy according to their best interests (for a historical and contemporary summary of Australian electricity policy see Chester and Elliot, 2019), this research provides useful insights to policy makers. Understanding residents' preferences and WTP for the different sources may suggest potential consumer surpluses and levies that could be employed to support the development costs for the preferred energy source in each state/territory.

The next section provides a closer look at the energy situation in the different states and territories of Australia. Next, a brief overlook at the questionnaire employed to collect the data (only relevant parts for this research) and the methodology employed in this research are reported. After presenting sample characteristics and the results of a latent class – latent variables model, the discussion provides support for the policy makers who aim at increase the share of energy produced from renewable sources. Finally, the conclusion section summarises the main finding of this research.

2. The case of Australia

2.1 National overview

This section provides a brief outlook on Australia's government status and on the main differences occurring amongst states and territories in terms of energy production and consumption. However, for reasons of brevity, this section will not include technical and specific information about different agencies managing energy policies within states and territories as well as at a federal level.

Australia is a federal parliamentary constitutional monarchy composed of six states, New South Wales (NSW), Queensland (QLD), Victoria (VIC), Western Australia (WA), South Australia (SA), and Tasmania (TAS), and two territories, the Australian Capital Territory (ACT) and the Northern Territory (NT), which function as states in most respects. The federal government outlined broad guidelines to reach national energy related targets through the Energy White Papers in 2015 (Australian Government, 2015). The significance of renewable energy is highlighted in this document stating that "renewable energy is an important part of Australia's diverse energy mix and the Australian Government is committed to supporting a sustainable renewable energy sector. The Australian Government remains committed to a Renewable Energy Target (scheme) that allows sustainable growth in both small- and large-scale renewables so that 20 per cent of Australia's electricity demand in 2020 comes from renewable sources" (Australian Government, 2015). In terms of guidelines, the Australian Government confirmed support for household solar systems, establishing a new fund (over AUD$1 billion) towards the research, development and demonstration of renewable energy projects and requires a reduction of pressure on energy intensive trade exposed sectors in order to support Australian jobs.

Within these guidelines, Australian states and territories may develop their own policies autonomously. The autonomy is in part due to the large heterogeneity of the states and territories in terms of politics, resources, landscape and infrastructure, resulting in different management of energy related policies (for a deeper overview on states' energy-related policies and strategies see Clean Energy Council, 2019). Indeed, whilst the average percentage of energy derived by renewable sources in 2016-17 was approximately 16 percent in Australia, the different states and territories present very different mixes of energy sources. A summary of the energy consumption by source and state/territory is provided in Table 1 based on figures for the 2016 fiscal year.

In some cases, some states are well short of contributing to the national targets. For example, the NT and WA derive approximately three and eight percent of their energy from renewable sources, respectively. More in line with the national average are QLD, NSW and VIC, although between 70 and 80 percent of electricity consumed is generated from coal-fired sources within these states. In other cases, there may be a tendency to become complacent relative to the national targets. For example, SA and TAS rely mostly on renewable energy sources, with a share of 50 and 90 percent of green energy, respectively (Australian Energy Statistics, 2018).

Table 1: Summary of electricity generation for the fiscal year 2016/2017 by type

RENEWABLE SOURCES	TAS	SA	NSW	VIC	WA	QLD	NT	AUS
Hydro	79.75%	0.03%	8.75%	1.81%	0.54%	0.98%	0.00%	6.35%
Wind	10.21%	37.39%	2.63%	6.78%	3.91%	0.04%	0.00%	4.80%
Solar PV	1.15%	8.66%	3.21%	2.36%	2.41%	3.35%	2.67%	3.10%
Biomass	0.25%	0.76%	1.16%	1.35%	0.47%	2.52%	0.00%	1.39%
Total renewable	**91.37%**	**46.84%**	**15.75%**	**12.30%**	**7.33%**	**6.90%**	**2.67%**	**15.65%**
NON- RENEWABLE SOURCES	**TAS**	**SA**	**NSW**	**VIC**	**WA**	**QLD**	**NT**	**AUS**
Coal	0.00%	0.00%	79.16%	82.54%	27.62%	72.06%	0.00%	62.23%
Natural gas	8.43%	52.16%	4.64%	4.90%	55.08%	19.46%	79.32%	19.70%
Oil products	0.20%	1.01%	0.45%	0.27%	9.97%	1.58%	18.00%	2.42%
Nuclear	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Total non-renewable	**8.63%**	**53.16%**	**84.25%**	**87.70%**	**92.67%**	**93.10%**	**97.33%**	**84.35%**

At the individual level, consumers are able to influence energy compositions directly by nominating the proportion of their energy provided from renewable resources when signing contracts directly with the energy provider. Packages can range from those with entirely no use of renewable resources to the entire supply coming from renewables with variation in prices. Energy suppliers also compete in terms of the nature of their renewable resources (e.g., generating only from solar sources; using hydro only). The target set by the Australian government is nation-wide and therefore it is important to explore the preferences of the Australian citizens residing in each state with regards to the *national* energy mix composition.

2.2 Non-renewable energy in Australian states and territories

Australia has extensive non-renewable energy resources, including oil, coal and natural gas, accounting for about 84 percent of all the energy produced in the fiscal year 2016/2017 (Australian Energy Statistics, 2018). The country is a larger producer and exporter of *coal* worldwide, being mined in every state. Therefore, it is not surprising that most energy produced is derived from this source (more than 60 percent) nationally (Resources and Energy Quarterly, 2019). However, large differences emerge amongst states and territories, with VIC, NSW and QLD producing more than 70 percent of their energy from coal whilst SA, TAS and NT are largely coal-free.

Australia is also the second largest exporter of *liquefied natural gas* (LNG) in the world, registering a 22 percent increase in the export volumes in 2018 with respect to the previous year (Resources and Energy Quarterly, 2019). The major gas basins are in QLD, NT and WA, however the energy derived by LNG only accounts for approximately 20 percent of the total production in QLD compared to about 80 and 55 percent in NT and in WA respectively (Australian Energy Statistics, 2018).

Nationally, only about two percent of energy produced is derived from *oil products*. Although around two thirds of Australia's production comes from an offshore basin in WA, the NT relies more than any other state or territory on the energy produced by this source (around 18 percent). The percentage of energy derived by oil products in WA is about 10 percent, whilst is almost null in the remaining states and territories.

Finally, even though Australia hosts about 33 percent of the world's uranium deposits and is the world's third largest producer of uranium, nuclear power stations have never been built in the country. By federal law, nuclear power generation is prohibited in Australia, although debate on this topic continuous to this day (see for instance Bird *et al.,* 2014; Ogilvie-White, 2015; Diesendorf, 2016).

2.3 Renewable energy in Australian states and territories

According to the Clean Energy Council, the generation of energy from renewable sources has increased rapidly in Australia over the past few years, driven mainly by heavy investments in wind and solar projects. In 2018, the increase in investments in large-scale energy projects has doubled with respect to the previous year (Clean Energy Council, 2019).

Energy generated by *wind* farms represents the fastest growing renewable source in Australia. The potential is mainly in the south of the continent, which lies in the path of the westerly wind 'roaring forties'. Taking advantage of their perfect locations, SA and VIC are the leader producers of wind energy across Australia, generating about 35 and 28 percent of the national production respectively.

Since the early 20th century, *hydro* has been the largest source of renewable energy in Australia, consistently providing approximately five to seven percent of Australia's overall electricity generation over the last several decades. The biggest hydroelectricity scheme is the Snowy Mountains Scheme (in NSW) which accounts for approximately half of Australia's total hydroelectricity generation capacity (Clean Energy Council, 2019). However, hydro energy accounts only for about seven percent of NSW's energy. Conversely, about 80 percent of Tasmania's electricity is generated by hydro (Australian Energy Statistics, 2019).

The Australian Government has introduced programmes to stimulate the *photovoltaic* (PV) market in recent years, reaching an average penetration over the 20 percent in the residential sector. Nowadays, Australia is one of the top countries for installed PV capacity, ranked eighth amongst the members of the International Energy Agency (IEA, 2018). In QLD and SA, more than 30 percent of dwellings have solar panel installed. QLD also has the highest generation capacities, followed by NSW and VIC, whilst NT, ACT and TAS generate very little energy from this source (Australian PV Institute, 2019).

Biomass energy accounted for about seven percent of total clean energy generated in Australia in 2018 and just 1.5 percent of total electricity. QLD has the largest bioenergy sector amongst the states and territories, with its power stations accounting for more than half of the country's generation potential (Clean Energy Council, 2019; KPMG, 2018). On the other hand, the production of biomass energy in NT, TAS, WA and SA is almost nil (Australian Energy Statistics, 2019).

3. Design of the study and methodological approach

3.1 The survey

An online survey was developed and administered through the online platform Qualtrics (Qualtrics, Provo, UT) and distributed by two external panel companies during a three weeks period from mid-September 2018. The questionnaire consisted of two main sections, a CE and an attitude scale , in addition to socio-demographic questions.

The CE comprised three tasks in which each respondent chose amongst three different policies representing different energy generation mixes in Australia. Policies were described by ten attributes indicating the percentage of energy generated by eight energy sources (namely hydro, solar, biomass, wind, oil, coal, gas and nuclear), the reliability (measured in minutes of blackouts per quarter) and the quarterly household cost. Whilst one alternative was fixed and represented the status quo, the attribute levels of the remaining two alternatives varied across the choice tasks according to a Bayesian D-efficient design (see e.g., Scarpa and Rose, 2008) with a blocking strategy. In generating the design, the status quo alternative represented the current energy mix for the Australian-wide market (Australian Energy Statistics, 2018). For the two non-status quo alternatives, the nuclear attribute could take values of 0, 5, 10, 15 or 20 percent, whilst the remaining renewable energy mix attributes were shifted from their base levels an amount between minus two and five percent. The non-renewable energy mix attributes where shifted from their base amounts between -20 and 7.5 percent. The process resulted in energy mixes greater than or less than 100 percent. Hence, the resulting energy mixes were recalibrated to 100 percent preserving the relative mixes derived after the percentage shifts were applied to the design. The final balanced energy mixes were used in optimising the design. The reliability attribute was varied between zero and 480 in increments of 60 minutes. Finally, the cost attribute was varied from the respondent self-reported energy bill by between minus ten and 30 percent. Uninformative priors in the form of uniform distributions were used, with the bounds selected so that the average utility for each attribute was balanced, such that no attribute was given a greater weight when generating the design. One thousand Halton draws were used to optimise the design. The final Bayesian D-error for the design was 0.895.

The final design had 36 choice tasks, which were blocked into 12 blocks of size 3. Given the final design was non-orthogonal, blocking was achieved by minimising the maximum absolute correlation obtained for each design attribute and the blocking column. The absolute value of the maximum correlation was 0.038 between the cost of the first non-status quo alternative and the blocking column. An example of choice task is shown in Figure 1.

	Supply characteristic	Current mix in AUS	Policy A	Policy B
ENERGY MIX COMPOSITION	Hydro	6.35%	6.66%	8.26%
	Solar	3.10%	1.00%	9.10%
	Biomass	1.39%	0.36%	1.57%
	Wind	4.80%	8.87%	3.14%
	Oil products	2.42%	2.19%	2.72%
	Coal	62.23%	58.58%	47.45%
	Gas	19.70%	22.36%	27.76%
	Nuclear	0.00%	0.00%	0.00%
RELIABILITY	Minutes of blackout	320	360	240
COST	Quarterly cost	$175	$158	$201
CHOICE		Current	Policy A	Policy B

Figure 1: example of choice task

The second section of the questionnaire included questions aimed at measuring the attitude towards the environment. The scale used was the revised New Ecological Paradigm (NEP) scale, developed by Dunlap *et al.* (2000), which consists of 15 items such that the agreement indicated using a Likert scale with the eight odd-numbered items reveals a pro-environmental attitude (NEP^{+}) and agreement with the seven even-numbered items supports a non-pro-environmental attitude (NEP^{-}).

3.2 Latent class model with latent variables

Latent class models (LCM) segment the population according to the different individuals' choice behaviours, explained by different perceptions of the attributes of the alternatives, different socio-demographic characteristics or different decision protocols. In this research, respondents are classified in the different segments (or classes) also according to their attitude towards the environment. In this section, the multiple indicator multiple cause (MIMIC), the class assignment and the choice models are outlined.

The MIMIC model consists of a set of simultaneous equations in which a latent variable (LV) is measured by multiple indicators (items of the Likert scale), defining the measurement model, and regressed on several observable exogenous variables (commonly, socio-demographic individuals' characteristics), outlining the structural model (Jöreskog and Goldberger, 1975). An insight on the structure of the MIMIC model has been obtained through a factor analysis, which has suggested the existence of two separate factors following the nature of the scale developed by Dunlap *et al.* (2000). The structural equations defining the two latent variables for individual *n* are:

$$NEP_n^{+} = \Gamma^{+} Z_n + \zeta_n^{+}, \text{ where } \zeta_n^{+} \sim N(0, \sigma_{\zeta^{+}}) \tag{1a}$$

$$NEP_n^{-} = \Gamma^{-} Z_n + \zeta_n^{-}, \text{ where } \zeta_n^{-} \sim N(0, \sigma_{\zeta^{-}}) \tag{1b}$$

The impact of the individuals' characteristics Z_n on the latent variables is measured through the LV-specific vector of parameters Γ, whilst ζ_n is a stochastic term representing the idiosyncratic impact on the LVs.

The items of the NEP scale load onto the two latent variables according to equations (2a) and (2b):

$$k_{i,n} = \lambda_i NEP_n^{+} + \varepsilon_{i,n}, \text{ where } i = 1,3,5,7,9,11,13,15 \tag{2a}$$

$$k_{j,n} = \lambda_j NEP_n^{-} + \varepsilon_{j,n}, \text{ where } j = 2,4,6,8,10,12,14 \tag{2b}$$

As supported by both exploratory and confirmatory factor analysis, the odd (even)-numbered items load onto NEP_n^{+} (NEP_n^{-}) by means of the loadings $\lambda_i (\lambda_j)$. The error terms ε_n are distributed as extreme value type 1 over the population. In line with the categorical nature of the items and according to the error distribution, an ordered logit model is used to model the attitudinal responses. The unconditional probability of observing individual *n* selecting the vector of responses K_n is:

$$P(K_n) = P(K_n^{+})^{*} P(K_n^{-}) = \int_{\zeta^{+}} \int_{\zeta^{-}} P(K_n^{+} | NEP^{+})^{*} P(K_n^{-} | NEP^{-}) dF_{\zeta^{+}} \zeta^{+} dF_{\zeta^{-}} \zeta^{-} \tag{3}$$

where $F_{\zeta^{+}} \zeta^{+}$ and $F_{\zeta^{-}} \zeta^{-}$ are the distributions of ζ^{+} and ζ^{-}, respectively.

Figure 2 shows graphically the relationships included in the MIMIC model.

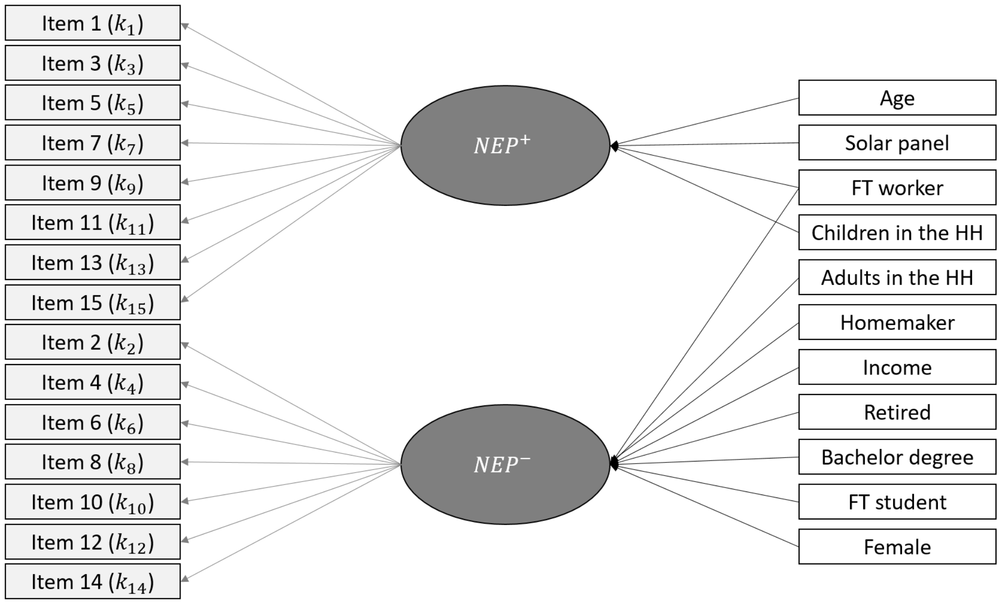

Figure 2: Structure of the MIMIC model

The different individuals' choice behaviours are captured in the LCM by means of class-specific utility functions. The effect of the attributes $X_{n,s}$ on the individual (*n*) utility functions is measured through the class-specific (*c*) set of parameters B^c, which is generic for the choice task *s*.

The utility functions of the DCM are reported in equations (4a), (4b) and (4c):

$$U_{n,1,s}^c = V_{n,1,s|c}^c + \nu_{n,1,s}^c = SQ^c + B^c X_{n,1,s} + \nu_{n,1,s}^c \tag{4a}$$

$$U_{n,2,s}^c = V_{n,2,s|c}^c + \nu_{n,2,s}^c = B^c X_{n,2,s} + \nu_{n,2,s}^c \tag{4b}$$

$$U_{n,3,s}^c = V_{n,3,s|c}^c + \nu_{n,3,s}^c = B^c X_{n,3,s} + \nu_{n,3,s}^c \tag{4c}$$

The first utility function represents the status quo alternative, whilst the remaining functions embody hypothetical energy mixes. The set of attributes $X_{n,s}$ includes the share of energy derived from the different sources as well as cost and reliability. However, in order to guarantee the identification of the parameters, the share of energy generated by coal is left out of the utility function (the sum of shares of the different sources is constant and equal to 100). Finally, the error terms $\nu_{n,s}^c$ are i.i.d. extreme value type 1. The individual conditional (on the class *c*) choice probability is:

$$P_{n|c} = \prod_a \prod_s \left(\frac{\exp(V_{n,a,s|c})}{\sum_{a \in A} \exp(V_{n,a,s|c})} \right)^{y_{n,a,s}} \tag{5}$$

where $y_{n,a,s}$ is an indicator variable that assumes the value of 1 if individual *n* chose alternative *a* in choice task *s* and 0 otherwise.

The choice probabilities in equation (5) depend on the class assignment. The utility functions of the class assignment model are given by

$$Class_{n,1} = Cl_{ASC} + \Theta_1 Z_n + \Phi^+ NEP_n^+ + \Phi^- NEP_n^- + \xi_{n,1} \tag{6a}$$

$$Class_{n,2} = \Theta_2 Z_n + \xi_{n,2} \tag{6b}$$

The observed component of the utility, $V_{n,c}^{cl\_as}$, consists of the sum of an alternative specific constant, Cl_{ASC}, a set of sociodemographic variables including age, gender, education, party voted at the last federal election and residence and the two latent variables defined in the MIMIC model. The vector Θ contains the parameters measuring the effect of the sociodemographic characteristics Z_n on the class assignment utility functions, whilst Φ^+ and Φ^- are the parameters associated with the latent variables. Finally, the error terms ξ_n are i.i.d. extreme value type 1. The unconditional (on the latent variables) probabilities of the assignment model are:

$$P_{n,c=1} = \int_{\zeta^+} \int_{\zeta^-} \frac{\exp(V_{n,c=1}^{cl\_as})}{\exp(V_{n,c=1}^{cl\_as}) + \exp(V_{n,c=2}^{cl\_as})} dF_{\zeta^+}\zeta^+ dF_{\zeta^-}\zeta^- \quad (7a)$$

$$P_{n,c=2} = 1 - P_{n,c=1} \quad (7b)$$

Following (5) and (7a-b), the complete individual probability is given by:

$$P_{n_{LCM}} = \int_{\zeta^+} \int_{\zeta^-} P_{n,c=1} * P_{n|c=1}{}^{y_{n,a,s}} + P_{n,c=2} * P_{n|c=2}{}^{y_{n,a,s}} \, dF_{\zeta^+}\zeta^+ dF_{\zeta^-}\zeta^- \quad (8)$$

The parameters of the joint model of choice, class membership as well as MIMIC model can be simultaneously estimated by maximizing the likelihood function:

$$L = \prod_n P_{n_{LCM}} * P(K_n) \quad (9)$$

4. Results

4.1 The sample

Data collected consists of 1,732 respondents residing in the major states or territories in Australia. After a quality check of the responses, the total number of observations retained for the study is 1,530, with 201 observations dropped for inconsistent responses or completion time lower than five minutes. Table 2 shows the number of respondents residing in metropolitan or rural areas of each state and territory.

Table 2: Frequencies by residence

	RESIDENCE								
	NSW	VIC	QLD	WA	SA	TAS	NT	ACT	TOTAL
Metro	8.56%	8.76%	6.27%	10.59%	9.15%	7.97%	6.21%	11.96%	**69.48%**
Rural	6.41%	3.66%	6.21%	2.61%	3.99%	4.38%	3.07%	0.20%	**30.52%**
Total	**14.97%**	**12.42%**	**12.48%**	**13.20%**	**13.14%**	**12.35%**	**9.28%**	**12.16%**	**100.00%**

A summary of the main socio-demographic characteristics is reported in Table 3. The sample is representative of the Australian population in terms of gender and residence in metropolitan/rural areas. However, the sample displays a higher median age than the Australian adult population (54 versus 45 years old) and a slightly lower median personal weekly income (median class is $400-$599 versus $662).

In order to represent the Australian population more precisely, the sample has been exogenously weighted according to the gender and the age of the Australian population.

Table 3: Characteristics of the sample

VARIABLE	CATEGORIES	SAMPLE	POPULATION
RESIDENCE	*Metropolitan*	69.61%	67.28%
GENDER	*Female*	50.07%	50.70%
AGE	*10th percentile*	30	20
	50th percentile	54	45
	90th percentile	72	74
INCOME	*10th percentile*	\$250 - \$399	n.a.
	50th percentile	\$400 - \$599	\$662
	90th percentile	\$1,600 - \$1,899	n.a.
OCCUPATION	*Student*	4.31%	-
	Employed	51.24%	50.51%
	Unemployed and Seeking	3.66%	2.72%
	Retired/Pensioner	29.54%	-
	Other	11.24%	-
EDUCATION	*Year 9 or below*	2.88%	8.00%
	High School	34.90%	31.40%
	Bachelor	29.80%	22.00%
	Post graduate	14.71%	
	Other	17.71%	28.20%
	Not stated	0.00%	10.40%

4.2 Results from the latent class model with latent variables

Table 4 reports the results for the latent class model with the latent variables: the left section of the table displays the MIMIC model (structural model on top and measurement model at the bottom) whilst the right section reports the coefficient estimates of the class assignment model (top right) and of the discrete choice model (bottom right).

The structure of the MIMIC model consists of two latent variables, labelled NEP^{+} and NEP^{-} defined by two sets of sociodemographic characteristics with specific parameters. The latent variable NEP^{+} (NEP^{-}) has a significant and positive (negative) impact on the odd (even)-numbered items of the Dunlap' *et al.*'s scale, representing therefore a (non) pro-environment attitude. Pro-environmental attitudes are predicted to be higher amongst those who are younger, have fewer children, have a solar panel installed on the house, are not employed full-time. In contrast, those with non-pro-environmental attitudes are more likely to be male, a housemaker or retired, do not have a bachelor degree, share the household with more adults, have a lower income and are not full-time workers or students. The role of these characteristics in explaining attitudes are largely consistent with other studies in the literature (e.g., Burke et al. 2014). As a result of the ordered logit model employed for the measurement equations in the MIMIC model, two sets of thresholds are reported at the bottom of the left section of Table 4.

The coefficients reported in the top right section of the table reveal that both socio-demographic characteristics and attitudes are important for assigning the respondents to the two classes. Resident of ACT, QLD, VIC and WA have a higher probability of belonging to Class 1, whilst South Australians are more likely to be included in Class 2. Residence in the remaining states (NSW, TAS and NT) does not significantly influence the assignment to any class. In terms of personal characteristics, gender, age, education and party voted at the last election (Green) significantly contribute to the class assignment. Finally, a higher score on the latent variable NEP^{+} (pro-environment attitude) increases the probability that the respondent is assigned to Class 1. The opposite is true for the latent variable NEP^{-} (attitude not in favour of the environment), for which a higher value corresponds to a larger probability for the respondent to being assigned to Class 2.

The coefficient estimates of the discrete choice model (DCM) suggest that the two classes have a strong opposite preferences in terms of alternatives presented in the CE: indeed, all else being equal, whilst respondents belonging to Class 2 reveal a strong preference for the status quo alternative, those assigned to Class 1 prefer the hypothetical alternatives. Both classes display a negative marginal utility for cost, suggesting that a lower cost is preferred. Class 2 also displays a negative marginal utility for reliability (less minutes of blackouts are preferred), whilst the same parameter for Class 1 is positive (very low). For identification issues, the parameter for Coal has chosen as a reference (note that the sum of all the sources amounts to 100 percent and therefore a degree of freedom is lost), meaning that the parameters for the different sources have to be interpreted with respect to Coal. For instance, all the else being equal, an increase of one percent in energy produced by Biomass, corresponding to a decrease of one percent of energy produced by Coal, increases the utilities of Class 1 and Class 2 by 0.183 and 0.927 respectively. Overall, respondents included in Class 1 prefer energy generated by biomass, hydro and solar over coal, whilst members of Class 2 prefer energy produced by biomass and wind, however coal is preferred to hydro and solar energy. The parameters of the DCM are better interpreted calculating the corresponding WTP measures reported in the next section.

Table 4: Coefficient estimates from LCM with latent variables. The values in brackets represent the robust t-ratio

MIMIC Model (structural model)		
	NEP⁺	*NEP⁻*
Age	-0.058 (-69.7)	
Bachelor degree		-0.360 (-9.13)
Female		-1.050 (-29.23)
Adults in HH		-0.540 (-32.35)
Children in HH	-0.453 (-18.03)	
Homemaker		0.800 (11.85)
Income		-0.001 (-30.67)
Retired		0.292 (4.23)
Solar panels	0.526 (13.69)	
Student FT		-2.140 (-27.1)
Employed FT	-0.479 (-12.23)	-1.180 (-26.54)
Sigma	2.510 (134.23)	2.350 (123.56)
MIMIC Model (measurement model)		
Item 1	fixed to 1	
Item 2		0.829 (198.46)
Item 3	0.817 (218.5)	
Item 4		0.636 (149.48)
Item 5	0.81 (213.1)	
Item 6		0.341 (47.08)
Item 7	0.651 (123.39)	
Item 8		fixed to 1
Item 9	0.608 (117.8)	
Item 10		0.989 (264.14)
Item 11	0.959 (286.13)	
Item 12		0.986 (225.22)
Item 13	0.796 (206.44)	
Item 14		0.75 (196.01)
Item 15	0.923 (256.14)	
τ1	-9.05 (-152.87)	-5.92 (-152.58)
τ2	-7.98 (-125.14)	-4.45 (-108.36)
τ3	-6.75 (-1463.2)	-3.17 (-1414.84)
τ4	-5.29 (-1504.68)	-1.87 (-841.35)
τ5	-3.29 (-1302.52)	-0.3 (-128.15)
τ6	-1.45 (-1117.37)	1.29 (482.09)

Class assignment		
	Class 1	*Class 2*
ASC	1.190 (13.1)	
Age		0.004 (3.57)
Female		0.064 (2.10)
High School		0.251 (7.63)
Green Party		0.268(7.84)
ACT	0.514 (4.94)	
QLD	0.179 (3.97)	
SA		0.227 (4.53)
VIC	0.427 (10.69)	
WA	0.190 (3.15)	
NEP⁺	0.125 (14.68)	
NEP⁻		0.056 (6.13)
Choice Model		
Status quo	-1.910 (-58.62)	1.350 (27.11)
Bio	0.183 (15.46)	0.927 (15.41)
Hydro	0.022 (8.53)	-0.236 (-16.2)
Wind	-0.005 (-1.27)	0.099 (4.36)
Solar	0.027 (8.19)	-0.112 (-10.53)
Gas	-0.017 (-16.12)	-0.001 (-0.17)
Oil	0.018 (5.80)	-0.138 (-11.00)
Nuclear	-0.028 (-18.23)	-0.069 (-17.32)
Coal	reference	reference
Cost	-0.002 (-10.18)	-0.007 (-16.16)
Reliability	0.000 (5.46)	-0.001 (-6.38)

4.3 Willingness to pay

The parameters reported in Table 4 represent the population level estimates and characterize the unconditional parameters assigned to each individual depending on the class assignment model only. Otherwise stated, these parameters indicate the preferences at the population level given the two classes and no information on the individual specific preferences can be inferred simply by these coefficients. However, using Bayes theorem, it is possible to compute the individual specific parameter estimates (see Greene and Hensher, 2003) such that:

$$\beta_n = \frac{P_{n|C1}\,{}^{*}P_{n,C1}}{P_n}\,{}^{*}\beta^{C1} + \frac{P_{n|C2}\,{}^{*}P_{n,C2}}{P_n}\,{}^{*}\beta^{C2} \tag{10}$$

where $P_{n|C1}$, $P_{n|C2}$ are calculated using equations (5), $P_{n,C1}$, $P_{n,C2}$ follow equations (7a-b) and $P_n = P_{n|C1}\,{}^{*}P_{n,C1} + P_{n|C2}\,{}^{*}P_{n,C2}$. Because of the presence of latent variables, 5,000 MLHS draws have been used to simulate the individual probabilities.

Table 5 reports the WTP for the different energy sources for each Australian state: after simulating the individual estimates for our sample, the individual WTPs have been averaged according to the residence. The willingness to pay measures represent a 10 percent increase or decrease compared to the current national energy generation (except for nuclear, where the amount is fixed to one percent).

Regardless of the residence, Australians are willing to pay a similar amount of about $17 per quarter to trade off the share of energy produced by biomass in Australia by 10 percent compared to the current level with the same amount generated by coal, which is to say from 1.39 percent to 1.53 percent of the national generation levels.

All the states reveal a positive willingness to pay also for energy produced by solar panels or wind farms, however differences in the monetary contributions emerge. Residents of ACT are willing to pay the highest amount ($2.53 per quarter) to increase the share of solar energy from 3.10 percent to 3.41 percent and decrease the energy generated by coal by the same amount. Conversely, South Australians display the weakest preference for solar, willing to pay $0.80 per quarter for the same trade-off, but the highest preference for energy generated by wind farms, which translates into a WTP of $2.18 to support an increase from 4.80 percent to 5.28 percent (with a decrease of the same amount in energy derived by coal).

Energy produced by hydro plants is desired only by residents of VIC and ACT, who are WTP $0.30 - $0.35 respectively per quarter to trade off 0.64 percent of energy derived by coal with the same amount generated by hydro plants. Remaining states display a negative preference for hydro, such that residents QLD, NSW, TAS, SA, NT and WA would be WTP to increase the share of energy derived by coal and decrease that generated by hydro plants (from a minimum of $0.59 to a maximum of $4.68 per quarter).

Energy derived by oil is preferred to that generated by coal in QLD, VIC, NT, WA and ACT, where residents are WTP from $0.21 to $0.70 per quarter to increase the share of energy extracted by oil from 2.42 percent to 2.66 percent and decrease that obtained by coal by the same amount. Opposite preferences are displayed by residents of NSW, TAS and SA, who would be willing to pay from $0.15 to $0.56 to increase the share of energy produced by coal at the expense of energy obtained by oil.

Energy derived by coal is preferred to that produced by natural gas across all the Australian states: WTPs range from $11.88 in SA to $15.47 in ACT per quarter to decrease the share of energy produced by natural gas from 19.70 percent to 17.73 percent (and increase that generated by coal by the same amount).

The least preferred source of energy is nuclear, for which residents all across Australia display a negative WTP ranging from $14.44 to $15.92. It is worth noting however that there currently exists no nuclear energy in Australia, despite some respondents believing this not to be the case. Finally, in spite of a positive coefficient for the reliability attribute displayed in Table 4 for Class 1, the individual specific parameter estimates suggest that Australians would be willing to pay from $0.02 (in VIC and ACT) to $0.05 (in SA) to reduce one minute of blackout per quarter.

Table 5: WTP for different sources and reliability

	WILLINGNESS TO PAY FOR A 10% TRADE-OFF WITH ENERGY GENERATED BY COAL (compared to the current national generation)							
	BIOMASS (1.39%)	**HYDRO (6.35%)**	**SOLAR (3.10%)**	**WIND (4.80%)**	**GAS (19.70%)**	**OIL (2.42%)**	**NUCLEAR (0%)**	**Blackout (min/quarter)**
TAS	$17.37	-$3.07	$1.35	$1.74	-$13.03	-$0.16	-$14.92	-$0.04
SA	$17.42	-$4.68	$0.80	$2.18	-$11.88	-$0.56	-$14.44	-$0.05
NSW	$17.36	-$3.04	$1.36	$1.73	-$13.05	-$0.15	-$14.92	-$0.04
VIC	$17.24	$0.30	$2.52	$0.82	-$15.44	$0.69	-$15.91	-$0.02
WA	$17.31	-$1.43	$1.92	$1.29	-$14.20	$0.25	-$15.40	-$0.03
QLD	$17.31	-$1.61	$1.85	$1.34	-$14.07	$0.21	-$15.35	-$0.03
NT	$17.28	-$0.59	$2.21	$1.06	-$14.81	$0.47	-$15.65	-$0.03
ACT	$17.24	$0.35	$2.53	$0.80	-$15.47	$0.70	-$15.92	-$0.02
AUS	$17.32	-$1.81	$1.79	$1.40	-$13.93	$0.16	-$15.29	-$0.04

Note: The values in brackets represent the current share of energy in the national mix. States are sorted in descending order of current energy generation from renewable sources.

Additional graphs displaying the distribution of the WTP values for the different energy sources and the different states and territories have been inserted in an online dashboard created using the package Shiny of the software R (Figure 3). The dashboard can be consulted at "…" (the link will be made public after the review process).

Figure 3: online dashboard

5. Conclusions and policy implications

The current research sort to examine the support and estimated WTP for renewable energy in the Australian context. Of note, the research sought to consider WTP across different energy sources and to further consider variation across the states and territories using an Australia wide sample. A discrete CE was used to gather data for this purpose whilst a choice model with latent classes and latent variables was able to account for consumer preference heterogeneity across various geographic, sociodemographic and attitudinal characteristics.

Evidence from the stated preference experiment shows that, overall, Australians are willing to pay more for a cleaner energy mix. There is considerable support amongst all consumers, irrespective of state or environmental attitudes and other characteristics, in their support for energy to be generated by biomass sources despite currently representing 1.4 percent of energy generated at the national level and no more than 2.5 percent in anyone state. There is also overwhelming objection to the use of nuclear energy at all levels, which currently remains prohibited in Australia despite the country holding 33 percent of the world's uranium deposits and being the world's third largest producer.

However, the dissonance between national and states policies and objectives may act as hindrance to the achievement of the goal set for the Paris agreement. Indeed, whilst Australia as a whole should notably increase the share of energy derived by renewable sources nation-wide, energy-related policies are implemented at state level. Accounting for such differences is an important input for policy development in Australia. The dissonance in Australia is evident for instance when looking at the WTP for increasing the share of energy produced by hydro plants. An analysis of the national preferences would suggest that, overall, Australians prefer energy derived coal over hydro (WTP equals to -$1.81), however residents of Victoria and Australian Capital Territory would be willing to pay a higher energy bill to substitute hydro power with coal fired energy. A similar (but opposite) dissonance also emerges for energy generated by oil. The need for such insights could be generalised to other countries composed by several states, such as United States of America or United Kingdom, that present large heterogeneity in terms of resources and residents' preferences and that signed the Paris Agreement as a unique body.

This research provides a useful mapping of Australian residents across all the states in terms of preferred energy sources and indicates which sources would have a higher chance of being economically supported by the local population. Whilst the energy mixes of some states, such as Tasmania and South Australia, include mostly renewable energy, an increment of RES will be beneficial for the country in states such as Western Australia or Northern Territory. State policies might have a higher chance to succeed and support the national goal if they comply with residents' preferences. For instance, residents of Western Australia and Northern Territory would strongly support investments in biomass, photovoltaic and wind farms, but would not want hydro power. This result is consistent with Ma' and Burton's (2016), who found that Western Australians mostly prefer solar energy, although it is noted that biomass energy was not explored in their work.

We also note critical individual differences in support for energy sources and the status quo at the state level. One latent segment emerging from the data were more supportive of change from the status quo, as well as greater support for the use of solar and hydro; such consumers were likely to be hold pro-environmental attitudes. In contrast, a second latent segment with negative pro-environmental attitudes were more likely to support the use of wind. Both segments were in agreement in the use of bio and both segments were against the use of nuclear energy.

Finally, we would strongly recommend investigating the specific renewable energy sources separately rather than having them grouped together in a single category "renewable sources" as it often happens in the literature. Indeed, our research indicates how policy makers can receive valuable insights from understanding the preferences of the residents of different states and territories for specific renewable sources rather than aggregate over sources of energy or not accounting for differences arising from governing structures, geographic location, attitudinal or sociodemographic characteristics.

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