Social acceptability of standard and behavioral economic inspired policies designed to reduce and prevent obesity

Emily Lancsar | Jemimah Ride | Nicole Black | Leonie Burgess

Correspondence
Emily Lancsar, Department of Health Services Research and Policy, Research School of Population Health, Australian National University, Canberra, Australian Capital Territory, Australia.
Email: Emily.Lancsar@anu.edu.au

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Abstract
The obesity epidemic is a significant public policy issue facing the international community, resulting in substantial costs to individuals and society. Various policies have been suggested to reduce and prevent obesity, including those informed by standard economics (a key feature of which is the assumption that individuals are rational) and behavioral economics (which identifies and harnesses deviations from rationality). It is not known which policy interventions taxpayers find acceptable and would prefer to fund via taxation. We provide evidence from a discrete choice experiment on an Australian sample of 996 individuals to investigate social acceptability of eight policies: mass media campaign; traffic light nutritional labeling; taxing sugar sweetened beverages; prepaid cards to purchase healthy food; financial incentives to exercise; improved built environment for physical activity; bans on advertising unhealthy food and drink to children; and improved nutritional quality of food sold in public institutions. Latent class analysis revealed three classes differing in preferences and key respondent characteristics including capacity to benefit. Social acceptability of the eight policies at realistic levels of tax increases was explored using post-estimation analysis. Overall, 78% of the sample were predicted to choose a new policy, varying from 99% in those most likely to benefit from obesity interventions to 19% of those least likely to benefit. A policy informed by standard economics, traffic...
The obesity epidemic is a significant public policy issue facing the international community. Obesity is associated with an increased risk of type 2 diabetes, hypertension, coronary artery disease, and cancer among other conditions (Kopelman, 2007), resulting in a considerable loss of wellbeing and an increased burden on the health system (Cawley & Meyerhoefer, 2012). The socioeconomic gradient associated with obesity means that the obesity epidemic has serious implications for widening social inequalities (e.g., McLaren, 2007). Despite considerable research and policy attention, obesity rates continue to rise with no sign of reversing (Ng et al., 2014), suggesting the need for innovative ways to try to counter the epidemic, including how we might increase the implementation of strategies that have evidence of efficacy.

Governments around the world use public policy to influence behavior, and economic incentives play a key role in this endeavor. While there are many ways to classify obesity policies, here we classify policies according to whether their underlying assumptions fit within (1) a standard economics framework or (2) are informed by behavioral economics (which we further classify as (2a) 'nudge' and (2b) 'budge' type policies—each defined below), in recognition of the importance of behavior, choice, and incentives in this area.

A cornerstone of standard economic theory is the assumption that individuals are rational and make choices that are consistent with their long-term welfare. A standard economics approach seeks to provide the rational decision maker with full information on the consequences of alternative actions, or to change the balance of benefits and costs for the individual and hence shift consumption of a good to a more socially optimal level (to correct for negative externalities and internalities) (Allcott et al., 2019). For example, standard neoclassical economics suggests that one way to change consumption of a good or service is to change its relative price by applying a tax or subsidy, enacted in policies such as taxes on sugar sweetened beverages (World Cancer Research Fund International, 2018), or a ‘fat tax’ (Bødker et al., 2015). Such taxes are argued to correct for negative externalities of obesity, particularly healthcare costs of obesity which are largely borne by public or private health insurance and hence by non-obese members of society (Cawley, 2015). Other examples in obesity policy include food labeling requirements and media campaigns to inform people about nutrition and physical activity.

More recently, other economic theories have called the assumption of rationality into question and proposed alternative explanations of behavior leading to obesity. A divergence between an individual’s choices and their welfare may arise due to imperfect information, time-inconsistent preferences, or imperfect rationality (Cawley, 2015), with a posited dual decision model of ‘deliberative’ (rational) and ‘affective’ (susceptible to mistakes) systems contributing to obesity (Ruhm, 2012). Behavioral economics has characterized a number of systematic anomalies in choice behavior including: status quo bias, loss aversion, priming, hyperbolic discounting and anchoring (McDonald, 2005; Thaler & Sunstein, 2008; UK Cabinet Office & Institute for Government, 2010). Harnessing these anomalies, “going with rather than against the grain of how people behave” (UK Cabinet Office & Institute for Government, 2010), it is possible to design policy interventions with the objective of altering the choice environment to facilitate individuals making more socially desirable choices (Thaler & Sunstein, 2008). Behavioral economics posits alternate explanations of the behavior leading to the rise of obesity, and suggests different approaches to prevent and reduce obesity (Oliver, 2011; UK Cabinet Office Behavioral Insights Team, 2010) potentially offering different tools for the policy makers’ tool kit.

A behavioral economics approach involves the design of interventions to harness or restrain systematic choice anomalies, to encourage people to make decisions that prevent or reduce obesity. Perhaps the most well-known set of behaviorally informed obesity policies relate to ‘nudge’, but there are other types of obesity policies that are informed by behavioral economic insights. One characterization of these approaches is to separate ‘nudge’ from ‘budge’ (Oliver, 2018).
Nudge tries to alter the choice environment to counteract behavioral biases in favor of healthier choices, often focused on the narrow environment immediately surrounding the decision, and avoids restricting the individual’s options. By contrast, budge aims to address the ways that industry can seek to promote unhealthy consumption by exploiting behavioral biases. It uses regulatory approaches to address the broader, structural environment or mandates the implementation of behaviorally informed interventions (Smith & Toprakkiran, 2019). Examples of nudge-type policies include: modifying the built environment to encourage physical activity; utilizing pre-commitment strategies to commit to more healthy decisions; using payment mechanisms such as prepaid cards and vouchers to make the purchase of healthy options easier (UK Cabinet Office Behavioral Insights Team, 2010); or capitalizing on present-biased preferences by using financial incentives to provide more immediate rewards for healthy behavior (Marteau et al., 2009). For the individual who discounts future costs of obesity-related health problems, payment to engage in physical activity modifies the present costs and benefits of exercising today rather than putting it off to tomorrow. Budge-type obesity policies include banning junk food advertising to children, regulation to limit junk foods being positioned near supermarket cashiers, or mandating the proportion of healthy and unhealthy foods offered through vending machines. These aim to prevent industry behavior that would exploit behavioral biases of individuals leading to unhealthy consumption.

Adoption of a policy by governments or policymakers depends in part on its social acceptability to taxpayers and voters (Marteau et al., 2011; Marteau et al., 2008). This is particularly relevant given the markedly different mechanisms by which interventions based on behavioral and standard economics seek to influence behavior. For example, when do ‘acceptable nudges’ become ‘unacceptable shoves’ (Marteau et al., 2008)? Measuring social acceptability fits within a general trend toward increasing public involvement in priority setting and accounting for social preferences in public policy. Policy interventions are often publicly funded, suggesting policy makers are required, in part, to consider social preferences in the decisions they take. More generally, policy makers face a difficult challenge of prioritizing the large number of potential interventions to reduce and prevent obesity. Some policies face vocal opposition, for example being labeled by their opponents as part of a ‘nanny state’ (Kersh, 2015). This could reflect widespread social unacceptability of those policies, but could also reflect the views of a vocal minority or the influence of private sector actors (such as the food industry) who seek to protect their business models (Jürkenbeck et al., 2020). Empirical evidence on social preferences for potential interventions will be helpful in informing such prioritization and in understanding the source of objections to policies.

This study addresses the question of the social acceptability of standard and behavioral economic inspired policies designed to reduce and prevent obesity. To do so, we employed a discrete choice experiment (DCE) in which respondents chose between obesity policy investment options, described by: one of eight policies; the policy’s effectiveness in terms of impact on future obesity rates; and the associated cost in terms of higher taxes. We investigated three policies informed by standard economics - mass media campaigns, traffic light nutritional labeling, and taxing sugar sweetened beverages - and five behaviorally informed policies - prepaid cards to purchase healthy food, financial incentives to exercise, improved built environment for physical activity, bans on advertising unhealthy food and drink to children, and improved nutritional quality of food sold in public institutions. Using latent class analysis, we found three classes with substantially different preferences for these policies, with membership of the preference classes differing in their likelihood of benefitting from obesity policies. Overall, at realistic levels of tax increases 78% of the sample were predicted to choose a new policy, but this ranged from 19% in those least likely to benefit from obesity interventions to 99% in those most likely to benefit. The most popular policy was inspired by standard economics (traffic light nutritional labeling) followed by behaviorally informed policies involving regulation of providers (junk food advertising bans and improvement of food quality in public institutions), while the least popular were behaviorally informed nudge-type policies targeting individuals (prepaid cards and financial incentives to exercise). This systematic elicitation of social preferences for behaviorally informed and standard economic policies designed to tackle obesity and the implied rank order of those policies add to the evidence base to inform responses to obesity. Our findings may also be useful beyond the scope of obesity policy to the ongoing consideration of the place for behavioral and standard economics to inform public decision making.

There has been some work on public attitudes to obesity policy (e.g., Jürkenbeck et al., 2020; Lund et al., 2011) using non experimental methods. Of the limited experimental literature, Gendall et al. (2015) used a best-worst object scaling task to explore which of 15 policies respondents thought would be most and least effective at reducing obesity (rather than to explore their preferences for the policies). That approach did not allow the policies to be decomposed into attributes and levels (as is standard in a DCE). Understanding which aspects of obesity policies are preferred by the public is key to informing decision-making, as this can facilitate development of policies that are effective and meet with public approval. Other studies have assessed the acceptability of attributes of individual policies but have not compared multiple policies (e.g., to inform implementation of sugar-sweetened beverage taxes - Blake et al., 2019; Cornelsen et al., 2020).
Promberger et al. (2012) used a DCE to explore preferences for a controversial policy, that of using financial incentives for weight loss and smoking cessation. They found the acceptability of financial incentives increased with the effectiveness of the rewards, and that incentives in the form of grocery vouchers were more acceptable than cash or luxury rewards. The current study is the first to use a DCE approach to explore social preferences for attributes of a range of policies encompassing those based on insights from both standard and behavioral economics. A DCE is well suited to investigating preferences for potential obesity policy interventions, since it can cover policies that have been enacted and those that have been proposed but not yet enacted. It offers insights not otherwise available since it is not usually feasible to obtain revealed preference data regarding the attributes of such policy interventions as there is no mechanism by which to observe public choices across policies.

The remainder of the paper is organized in four further sections. The next section describes our empirical study, including development of the survey instrument, the design of the DCE and the analytical strategy. Results are presented in Section 3, and discussed in Section 4 along with their policy implications and areas for further research while Section 5 concludes.

2 | METHODS

2.1 | Discrete choice experiments

DCEs are a stated preference approach regularly used in health economics (Lancsar & Louviere, 2008) and applied economics more broadly (Louviere et al., 2000). A key appeal of such methods is they allow a range of research questions to be addressed, some of which could not otherwise be answered with existing data sources. DCEs involve the generation and analysis of choice data and are usually implemented in surveys. Survey respondents choose between alternatives presented in choice sets—in our study between obesity policy investment options. Each alternative is described by a number of attributes which themselves are described by a range of levels (described below). The choices made are analyzed using discrete choice limited dependent variable models (Lancsar et al., 2017). The estimated choice models reveal respondent preferences regarding the policy investment options and the importance of attributes that describe those options. We harness the resulting model of preferences in post-estimation analysis to predict the uptake of each of the eight policy options (accounting for effectiveness and cost) to explore their social acceptability.

2.2 | Generation of the choice context, attributes, and levels

The general choice context and the attributes and levels of the alternatives between which respondents were asked to choose were generated from a review of the literature, discussion with obesity policy experts, and focus groups with members of the general public. Three focus groups with members of the public (n = 24) helped define the attributes and levels resulting in 3 attributes: policy type; impact on future obesity rates (in 2020); and cost in terms of higher taxes. Initially 12 policies were chosen to cover a range of policy types including: those inspired by behavioral and standard economics; population wide prevention; medical interventions; and those targeted at specific groups such as children, or low-income households. An online best-worst DCE in which respondents chose both the best and worst alternative per choice set was piloted in the Monash Behavioral Laboratory (n = 36) followed by one-to-one interviews with all participants. Respondents were members of the general public, not students. Key changes following the pilot were the reduction of the number of policy levels from 12 to 8, to: reduce cognitive burden; focus on those policies considered most salient; providing representation of different types of policies; and that could be implemented at a population level rather than being only delivered to a subset of the obese population (such as bariatric surgery). The final set of attributes and levels used in the full study are described in Table 1. The levels on the policy attribute included those that can be classified as: (1) informed by standard economics; (2a) nudge-type behaviorally informed; and (2b) budge-type behaviorally informed.

2.2.1 | Policies consistent with standard economics

Three policies were consistent with standard economics: (i) National mass media campaign to encourage healthy lifestyle choices; (ii) nutritional information labeling using traffic light symbols on the front of all packaged foods; and (iii) taxing
sugar sweetened beverages. The mass media campaign was described as focusing on positive messages that can produce positive changes in health-related behaviors, such as diet and exercise, or preventing negative changes in health-related behaviors across the Australian population. Traffic light labeling was described as involving mandatory labeling on the front of all packaged foods to indicate whether the levels of nutrients in a product (such as fat, saturated fat, salt, and sugar) are low (green), medium (orange) or high (red). Taxing sugar sweetened beverages (such as soft drinks) by an additional 20% (World Cancer Research Fund International, 2018) would increase their price. The first two policies provide information to help the rational decision maker make better food and physical activity decisions while the third aims to deter consumption by increasing prices.

2.2.2 | Nudge-type behaviorally informed policies

A further three policies were consistent with nudge-type behaviorally informed policies: (iv) Prepaid cards that can only be used to purchase healthy food in supermarkets (other less healthy food would still be available for purchase, but must be paid for separately using cash); (v) a payment incentive for the obese to increase physical activity, entailing a cash incentive to be paid to those who meet weekly physical activity goals; and (vi) funding changes to the built environment (such as extending bicycle paths, building bicycle parking stations, improving conditions for pedestrian travel, and investing in parks and indoor/outdoor sport facilities) to make physical activity safer and more accessible. These policies would preserve individuals’ autonomy but make use of behavioral biases to encourage healthier behavior (Oliver, 2018). The first two (prepaid cards and financial incentives) had a narrow focus on individual choices directly related to their nutrition or exercise. Prepaid cards harness the idea that different payment methods (cash, debit) can influence purchasing decisions. Since paying by cash makes the parting of money more visible and ‘painful’ compared with paying by a debit card, where transactions are less visible, prepaid cards can make it easier for people to make healthy food choices.

### TABLE 1  Attributes and levels

| Attribute                                      | Levels                                                                 |
|------------------------------------------------|------------------------------------------------------------------------|
| Policy type                                    | (1) Policies consistent with standard economics                         |
|                                                | • Nutritional information labeling using traffic light symbols           |
|                                                | • National mass media campaign to encourage healthy lifestyle choices    |
|                                                | • Tax sugar-sweetened beverages                                         |
| (2a) Nudge-type behaviorally informed policies | • Prepaid cards for healthy foods in supermarkets                        |
|                                                | • Payment incentive for the obese to increase physical activity         |
|                                                | • Funding for physical activity infrastructure and outdoor spaces      |
| (2b) Budge-type behaviorally informed policies | • Improve nutritional quality of foods sold in public institutions       |
|                                                | • Ban unhealthy food and drink advertising to children                  |

| Additional cost to you per year, paid as an increase in income taxes by: | $12 per year ($1 per month) |
|-------------------------------------------------------------------------|-----------------------------|
|                                                                         | $120 per year ($10 per month) |
|                                                                         | $240 per year ($20 per month) |
|                                                                         | $480 per year ($40 per month) |

| Impact on obesity rates in 2020*                                            | 32% will be obese in 2020 (no change to the projected obesity rate) |
|-----------------------------------------------------------------------------|-------------------------------------------------------------------|
|                                                                            | 31% will be obese in 2020 (moderate reduction in the projected obesity rate) |
|                                                                            | 29% will be obese in 2020 (large reduction in the projected obesity rate) |
|                                                                            | 28% will be obese in 2020 (very large reduction in the projected obesity rate) |

Note: Attribute levels are described in greater detail in Appendix 1.

*See Backholer et al. (2010).
and harder to make unhealthy food choices (Just et al., 2008). Paying individuals to engage in healthy behavior is increasingly being considered (Marteau et al., 2009) including in the context of nutrition and physical exercise (Paul-Ebboomhen & Avenell, 2008; Promberger et al., 2012). The policy of improvements to the built environment had a wider set of potential impacts, with benefits beyond obesity.

2.2.3 | Budge-type behaviorally informed policies

The final two policies were consistent with budge-type behaviorally informed policies: (vii) bans on unhealthy food and drink advertising to children and (viii) improving the nutritional quality of food offered in public institutions. These were behaviorally informed but focused on limiting the capacity for exploitation of people’s behavioral biases (Oliver, 2018). Advertising bans are proposed to reduce children’s awareness of and desire to consume unhealthy foods and help establish healthy eating patterns, and to limit the promotion of unhealthy food consumption via behavioral biases. Improving nutritional offerings in public institutions would introduce regulations to ensure that no more than 20% of foods sold in catering outlets and vending machines in schools, hospitals and community centers are ‘unhealthy’; or equivalently ensure that 80% of foods sold are healthy. This would constrain the options available to individuals to encourage them to choose from the more plentiful healthy options.

The levels of the effectiveness attribute (impact on obesity rates) were informed by previous modeling of feasible projections of obesity rates (Backholer et al., 2010). Cost levels were informed by discussion at the focus groups of willingness to pay for obesity policies. As noted below, each attribute was described in detail using Avatar narrated videos which have been successfully used to improve respondent understanding of attributes/levels and choice tasks (Lancsar et al., 2020). When completing the choice task, respondents could also access a glossary to remind themselves of the meaning of the attributes and levels (contained at Appendix 1).

2.3 | Experimental design and choice task

The decision of interest in each choice set was between a constant status quo and two generic alternatives (Policy A and Policy B). The status quo was described as no additional policy interventions would be funded, no cost and no change to the projected obesity rate (i.e., 32% would be obese in 2020). To generate the alternatives A and B per choice set, we started with the full factorial design in 128 rows (4 x 4 x 8). To be able to estimate all two-way interactions we applied two generators to create 256 choice sets (Street & Burgess, 2007). Importantly, this allowed broad coverage of the design space. In order to identify interactions, some choice sets necessarily included cost and effect levels the same across the alternatives A and B, but the 8 level policy attribute always differed across alternative A and B to maximize information obtained on policy preferences. In addition to the necessity to allow for interactions, having some attributes levels the same across alternatives also reduces cognitive burden. We blocked the 256 choice sets into 16 versions of 16 choice sets with respondents randomly assigned to versions. The design was balanced with each level of each attribute appearing approximately the same number of times in each block and in each alternative.

Following the pilot, the choice question was also changed to a best-best approach rather than a best-worst DCE for the full study preference elicitation task, to reduce cognitive burden (Ghijben et al., 2014). For the purposes of this paper, we harness data from the standard (first) choice from the full choice set only.

2.4 | Online survey and data collection

As can be seen from the glossary of policies (and attributes and levels more generally) contained in Appendix 1, some of the policies would have been very new to respondents. While the general topic of obesity is often in the popular press, respondents were unlikely to come to the survey with a detailed understanding of obesity, BMI, and related information. For this reason, we developed an avatar-narrated background to the online survey. The avatar explained the purpose of the survey, discussed obesity, its causes, associated adverse health outcomes, social patterning and costs, and policies designed to reduce or prevent obesity (see Appendix 2). It explained the choice task and each attribute in detail using pictures and diagrams. When making decisions in the choice sets, respondents could click on a link to see a textual glossary
to remind themselves of the meaning of each of the attributes (Appendix 1). Respondents were asked to consider any attributes not included in the description of the alternatives as constant across the alternatives.

An example choice set is contained in Figure 1. Each choice set contained two new policy alternatives and a constant status quo. A citizen framing was used: respondents were asked to suppose the Australian government is considering introducing new policies aimed at reducing obesity and is interested in learning about their preferences, as tax-paying citizens. Given this framing and the use of increase in taxes as the payment vehicle for the cost attribute, the survey was administered to a sample of taxpayers from an online panel, with invitees selected according to quotas to be representative of Australian taxpayers in terms of age and gender. Members of the online panel accessed an invitational web link, completed a set of initial screening questions to determine eligibility, and after watching and listening to the avatar-narrated background, completed 16 choice tasks followed by questions asking about the clarity of the task and a set of socio-demographic questions (see Appendix 4).

### 2.5 Analytical framework

#### 2.5.1 Choice models

Data from DCEs are modeled within a random utility theory framework which assume the utility respondent $i$ derives from choosing alternative $j$ in choice set $s$ is decomposed into

$$ U_{ij} = V_{ij} + \epsilon_{ij}; i = 1,..,N; s = 1,..,S; j = 1,..,J; $$

where $N$ denotes individual decision-makers, $J$ choice alternatives and $S$ choice sets. $V_{ij}$ represents the systematic component of the overall utility of choosing alternative $j$ and $\epsilon_{ij}$ is the stochastic disturbance term representing unobservable characteristics. This systematic component can be described in terms of the attributes of alternatives as follows.
\[ V_{ij} = \alpha_j + X_{ij} \delta \]  
(2)

where \( X_{ij} \) is a vector of attributes, including their interactions, describing alternative \( j \), and \( \alpha_j \) and \( \delta \) are parameters to be estimated. For \( \alpha_j \), we specified a common alternative specific constant (ASC) for choice of a new policy relative to the status quo. Sociodemographic characteristics are often interacted with the attributes of the alternatives to explore observed preference heterogeneity; as discussed below, we instead harness such characteristics to explain preference class membership in our latent class analysis.

We link the discrete choice \( y_{is} = j \) to the associated utilities by assuming individuals choose alternative \( j \) if and only if it delivers the highest utility in comparison with the utility associated with all other alternatives in the choice set. The probability of choosing an alternative is

\[ P_{isj} = \text{Prob}(y_{is} = j) = \text{Prob}(U_{isj} - U_{isl} > 0) \forall l \neq j. \]  
(3)

Assuming the stochastic disturbance terms are independently and identically distributed following an extreme value Type-I distribution leads to

\[ P_{isj} = \frac{\exp(\sigma V_{isj})}{\sum_{l=1}^{s} \exp(\sigma V_{isl})} \]  
(4)

where \( \sigma \) is the scale parameter (inverse of the standard deviation of the disturbance, routinely normalized to one). This is operationalized through the multinomial logit (MNL) model.

To explore heterogeneity in preferences in our sample, we estimated a latent class logit model (also known as a finite mixture model). Latent class logit extends the MNL model by allowing preferences for the choice alternatives, and attributes that describe them, to vary between respondents—for example, some people may have a strong preference for further investment in obesity reduction policies while others may not, or some people may strongly prefer a policy of traffic light labeling on food while others may not. In a latent class model preference heterogeneity is assumed to follow a discrete distribution, with a finite number of preference classes, so that preferences vary between but not within classes. We also estimated a class membership function in which we used socio-demographic covariates (age, gender, weight, self-assessed health, weight satisfaction, income, children, and attitudes to government responsibility for addressing obesity) to predict class membership. We defined \( V_{isj} \) as

\[ V_{isj} = \alpha_{jc} + X_{ijc} \delta_c \]  
(5)

where, as in equation (2), \( X_{ijc} \) is a vector of attributes, including their interactions, describing alternative \( j \), and \( \alpha_{jc}, \delta_c \) are parameters to be estimated, but unlike in equation (2) this is for each class \( c \). Within \( X_{isj} \), given the generic nature of the non status quo options in the choice sets, we estimated a common set of parameters across generic alternatives A and B, and we allowed for all two-way attribute interactions. As noted in relation to equation (2), for \( \alpha_j \), we specified a common alternative specific constant (ASC) for choice of a new policy relative to the status quo. The utility associated with the status quo was normalized to zero for identification. We also accounted for block effects via interacting with the ASC a series of dummy variables indicating to which design block an individual was randomized. If \( \pi_c \) is the probability of membership of class \( c \), and with \( V_{isj} \) incorporating class-specific parameters, the probability of choosing an alternative in the latent class model is given by

\[ P_{isj} = \sum_{c=1}^{C} \pi_c \left\{ \frac{\exp(\sigma V_{isj})}{\sum_{l=1}^{C} \exp(\sigma V_{isl})} \right\} \]  
(6)

Our analytical approach started with the estimation of an MNL model and determination of functional form on the basis of goodness of fit. In particular, we tested for higher order polynomials on cost and effect and all two-way attribute interactions. We used the implied preferred functional form in the estimation of the latent class logit model. We specified that the class membership model was a function of participant characteristics and selected the optimal number of classes based on the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) as well as precision of the parameter estimates with a range of 2-5 classes tested.
2.5.2 | Predicted probability analysis

Predicted probability analysis allows investigation of the relative impact of each of the attributes on choice (Lancsar et al., 2007) and more specifically in this study was undertaken to predict the uptake of each of the policy options accounting for effectiveness and cost. This allows exploration of social acceptability of the eight policies. In particular, we harnessed the parameter results (which provide the marginal utility response for each attribute) from the preferred choice model and set the policy type, effectiveness, and cost to particular values of interest and used equation (5) to predict the percentage uptake of each combination. Given uncertainty around the effectiveness of each policy, the analysis was undertaken assuming a 1 percentage-point improvement in obesity rates and redone assuming 4 percentage-point improvement in obesity rates. For each policy type, cost (in terms of higher taxes per taxpayer per month) was set to a value expected to be involved in implementing that policy. These were sourced from the literature and, where possible, existing policies. Further detail of feasible cost values for each policy are available in Appendix 3. Predictions were made by defining the nine alternatives (eight policies and the status quo) and predicting the alternative that would have the highest probability of choice for each individual, based on the estimated coefficients from the model and the predicted class membership for each individual. To explore distributional aspects, we also investigated how the predicted percentage of taxpayers that would choose a policy as best varied across key respondent characteristics including age, gender, income, weight, and weight satisfaction.

We also calculated the willingness to pay additional taxes for each policy to be implemented, at an effectiveness of 1 percentage-point improvement in obesity rates, using the Hicksian compensating variation calculated as follows:

$$CV = -\frac{1}{\lambda} \left[ \ln \sum_{j=1}^{J} e^{V_j^0} - \ln \sum_{j=1}^{J} e^{V_j^1} \right]$$

We proxy for $\lambda$, the marginal utility of income, using the additive inverse of the estimated coefficient on cost. $V_j^0$ is the value of the systematic component of the utility function calculated for a no-policy scenario, while $V_j^1$ is its value for each policy in turn (using the estimated coefficients from the model to calculate $V_j$).

3 | RESULTS

The sample comprised 996 respondents, representative of Australian taxpayers in age and gender, who completed the online survey in 2017. Sample characteristics are described in Table 2. Only 5% of the sample reported that it was difficult to choose the best option, with 62% reporting that it was an easy task. When asked what aspect of the effectiveness of the policies was foremost in their consideration, 30% reported that they thought about reduction in obesity itself, 23% reduction in associated health conditions, 18% reduction in health care costs, 22% improvement in overall wellbeing, and 6% another aspect of effectiveness.

3.1 | Choice model

Table 3 presents the results for the latent class logit model with all two-way interaction terms. The optimal number of classes based on AIC, BIC and precision of the parameter estimates was the three-class model. Appendix 5 presents goodness of fit figures for latent class models with two to five classes. A key distinguishing feature between the three classes was the likelihood of the members of each class benefitting from obesity policies. Class 3 (comprising 22% of the sample) could be seen as those least likely to benefit from obesity policies since they were less likely to be obese, older (and therefore less able to see long-term benefits from additional policy to reduce or prevent obesity), and also less likely to believe government holds some responsibility for addressing obesity in adults. Class 2 (40% of the sample) could be seen as those most likely to benefit since they were younger and more likely to be obese, and to believe that government holds responsibility for addressing obesity in adults and children. Class 1 (37% of the sample) were like class 2 except that they were less likely to be obese but were still motivated in that they were dissatisfied with their weight and believed in government responsibility for addressing obesity in adults. The parameter results in Table 3 are used as inputs to the prediction and WTP analysis discussed in the next section. Further interpretation of Table 3 results is provided in the Appendix.
|                           | Full sample | Class |   |   |   |   |   |
|---------------------------|-------------|-------|---|---|---|---|---|
|                           | No. | %    | No. | %    | No. | %    | No. | %    |
| **Gender**                |     |      |     |      |     |      |     |      |
| Female                    | 439 | 44%  | 186 | 46%  | 160 | 43%  | 93  | 42%  |
| Male                      | 557 | 56%  | 215 | 54%  | 214 | 57%  | 128 | 58%  |
| **Age**                   |     |      |     |      |     |      |     |      |
| 18–29                     | 206 | 21%  | 95  | 24%  | 76  | 20%  | 35  | 16%  |
| 30–44                     | 326 | 33%  | 126 | 31%  | 127 | 34%  | 73  | 33%  |
| 45–59                     | 320 | 32%  | 122 | 30%  | 118 | 32%  | 80  | 36%  |
| 60–74                     | 120 | 12%  | 46  | 11%  | 45  | 12%  | 29  | 13%  |
| 75+                       | 24  | 2%   | 12  | 3%   | 8   | 2%   | 4   | 2%   |
| **BMI category**          |     |      |     |      |     |      |     |      |
| BMI <20                   | 77  | 8%   | 27  | 7%   | 28  | 7%   | 22  | 10%  |
| BMI 20–25                 | 331 | 33%  | 113 | 28%  | 127 | 34%  | 91  | 41%  |
| BMI 25–30                 | 325 | 33%  | 135 | 34%  | 119 | 32%  | 71  | 32%  |
| BMI 30+                   | 263 | 26%  | 126 | 31%  | 100 | 27%  | 37  | 17%  |
| **Household income**      |     |      |     |      |     |      |     |      |
| 0–20,000                  | 10  | 1%   | 3   | 1%   | 4   | 1%   | 3   | 1%   |
| 20–40,000                 | 60  | 6%   | 26  | 6%   | 23  | 6%   | 11  | 5%   |
| 40–60,000                 | 171 | 17%  | 77  | 19%  | 53  | 14%  | 41  | 17%  |
| 60–80,000                 | 199 | 20%  | 71  | 18%  | 79  | 21%  | 49  | 20%  |
| 80–125,000                | 298 | 30%  | 125 | 31%  | 116 | 31%  | 57  | 30%  |
| 125–150,000               | 123 | 13%  | 46  | 11%  | 52  | 14%  | 25  | 12%  |
| 150–200,000               | 84  | 8%   | 32  | 8%   | 30  | 8%   | 22  | 8%   |
| 200,000+                  | 51  | 5%   | 21  | 5%   | 17  | 4%   | 13  | 5%   |
| **Self-assessed health**  |     |      |     |      |     |      |     |      |
| Excellent                 | 103 | 10%  | 39  | 10%  | 44  | 12%  | 20  | 9%   |
| Very good                 | 353 | 35%  | 148 | 37%  | 127 | 34%  | 78  | 35%  |
| Good                      | 373 | 37%  | 144 | 36%  | 139 | 37%  | 90  | 41%  |
| Fair                      | 135 | 14%  | 52  | 13%  | 51  | 14%  | 32  | 14%  |
| Poor                      | 32  | 3%   | 18  | 4%   | 13  | 3%   | 1   | <1%  |
| **Satisfaction with own current weight** |     |      |     |      |     |      |     |      |
| Very satisfied            | 129 | 13%  | 50  | 12%  | 47  | 13%  | 32  | 14%  |
| Satisfied                 | 338 | 34%  | 110 | 27%  | 138 | 37%  | 90  | 41%  |
| Neither                   | 192 | 19%  | 76  | 19%  | 63  | 17%  | 53  | 24%  |
| Dissatisfied              | 248 | 25%  | 116 | 29%  | 90  | 24%  | 42  | 19%  |
| Very dissatisfied         | 89  | 9%   | 49  | 12%  | 36  | 10%  | 4   | 2%   |
| Has at least one child living at home |     |      |     |      |     |      |     |      |
| No                        | 628 | 63%  | 256 | 64%  | 240 | 64%  | 132 | 60%  |
| Yes                       | 368 | 37%  | 145 | 36%  | 134 | 36%  | 89  | 40%  |
| **Believes government has at least some responsibility for obesity in adults** |     |      |     |      |     |      |     |      |
| No                        | 175 | 18%  | 36  | 9%   | 57  | 15%  | 82  | 37%  |
| Yes                       | 821 | 82%  | 365 | 91%  | 317 | 85%  | 139 | 63%  |
3.2 Prediction analysis

The figures in Table 4 are the predicted probability that each policy ‘package’, composed of a particular policy, level of effectiveness and additional cost, would be chosen as best if all nine policies were offered (the eight policies described above and the status quo of no new policy, no change in obesity rates and no additional cost). In terms of interpretation, recall from Section 2.5.2 that this analysis harnesses the parameter estimates from the estimated choice model (Table 3) combined with policy packages of interest, rather than specific combinations considered in the choice sets. So the predictions are based on the real-world values of cost and effectiveness associated with each policy.

Given the differing likelihood of benefiting from new obesity policy across the three latent preference classes, it is not surprising that (at effectiveness of a one percentage-point reduction in obesity rates) 99% of those most likely to benefit (class 2) and 90% of those described as motivated (class 1) were predicted to choose a new policy, while only 19% of those least likely to benefit (class 3) were predicted to choose a new policy. At effectiveness of a four percentage-point reduction in obesity rates, the results were similar with 24% of class 3, 96% of class 1, and over 99% of class 2 predicted to choose a new policy.

Looking at predictions across the full sample in Table 4 (using the sum of class-specific predictions weighted by class shares), even with only projected effectiveness of 1 percentage-point reduction in the obesity rate, overall 78% of the sample were predicted to choose a new policy, and 64% of the sample to choose a new policy that would entail paying more taxation. The overall implied preference order across the 8 policies from most to least preferred was:

1. Traffic lights (17.7%),
2. Advertising bans (11.1%),
3. Improve food quality in public institutions (10.6%),
4. Mass media campaign (10.2%),
5. Fund physical activity infrastructure (9.6%),
6. Tax sugar-sweetened beverages (8.8%),
7. Prepaid cards (4.9%),
8. Financial incentives to exercise (4.7%).

The remaining 22.2% were predicted to choose the status quo of no new policy. Across classes, there was a similar implied preference ordering of policies, except that for class 2 mass media campaign was ranked lower than for classes 1 and 3, for class 1 advertising bans was ranked lower than for classes 2 and 3, and for class 3 taxing sugar sweetened beverages was ranked lower than for classes 1 and 2.

To explore distributional considerations, a similar approach was used to generate predictions of the percentage for whom each policy had the highest probability of choice (among all policies) for the sample when the sample was divided by age, gender, income, weight, and weight satisfaction instead of class (results provided in Appendix 6). These results show a higher probability of choice for all policies among those with higher BMI, those dissatisfied with their weight, or in the youngest age band (19-35) and corresponding lower proportions predicted to choose no policy as best.

With the policies classified according to their underlying economic framework, from Table 4 we can see that the policies classified as (1) standard economics and (2b) budge were more popular, and those classified as (2a) nudge were the least popular. The exception was funding physical activity infrastructure, which ranked in the middle. While this can be classified as nudge, it differs from the other nudge-type policies in that it carries broader benefits beyond improving nutrition and physical activity for the individual, such as social connections through recreational sport, or reduced environmental harms through promoting cycling or walking. The policies with an underlying standard economic framework

### TABLE 3: Estimation results

| Policy                                                        | Class 1 b (se)   | Class 2 b (se)   | Class 3 b (se)   |
|---------------------------------------------------------------|------------------|------------------|------------------|
| **Alternative-specific constant: New policy [base: no policy]** |                  |                  |                  |
|                                                               | 0.060 (0.184)    | 1.867*** (0.133) | −2.609*** (0.372) |
| **Policies [base level: Mass media campaign]**                |                  |                  |                  |
| Traffic light labeling                                       | 0.144 (0.231)    | 0.906*** (0.139) | −0.824 (0.565)   |
| Prepaid cards                                                | −0.714** (0.250) | −0.535*** (0.143)| −3.262*** (1.196)|
| Advertising bans                                             | −0.283 (0.242)   | 0.302* (0.140)   | −0.045 (0.554)   |
| Improve food quality in public institutions                  | −0.047 (0.242)   | 0.224 (0.143)    | −0.939 (0.614)   |
| Fund physical activity infrastructure                        | −0.093 (0.227)   | 0.459*** (0.139) | −0.691 (0.636)   |
| Tax sugar-sweetened beverages                                | −0.218 (0.239)   | 0.107 (0.150)    | −3.014*** (0.909)|
| Financial incentives to exercise                             | −0.229 (0.248)   | 0.029 (0.147)    | −1.291 (0.904)   |
| Effectiveness – reduction in population obesity rate by 2020 (percentage points) | 0.302*** (0.058) | 0.365*** (0.036) | −0.055 (0.154)   |
| Cost per month (in additional taxes)                         | −0.075*** (0.010) | −0.035*** (0.004)| −0.038 (0.022)   |
| **Policy interactions with cost**                            |                  |                  |                  |
| Traffic light labeling                                       | 0.016 (0.011)    | −0.007 (0.005)   | 0.043 (0.027)    |
| Prepaid cards                                                | 0.015 (0.011)    | 0.005 (0.005)    | 0.038 (0.042)    |
| Advertising bans                                             | 0.021 (0.011)    | 0.002 (0.005)    | −0.100* (0.048)  |
| Improve food quality in public institutions                  | 0.005 (0.011)    | 0.003 (0.005)    | 0.003 (0.036)    |
| Fund physical activity infrastructure                        | 0.012 (0.010)    | 0.002 (0.005)    | −0.015 (0.033)   |
| Tax sugar-sweetened beverages                                | 0.028** (0.011)  | 0.001 (0.005)    | 0.060* (0.030)   |
| Financial incentives to exercise                             | 0.025* (0.011)   | 0.001 (0.005)    | −0.033 (0.062)   |
| **Policy interactions with effectiveness**                   |                  |                  |                  |
| Traffic light labeling                                       | 0.039 (0.069)    | −0.069 (0.041)   | 0.353 (0.187)    |
| Prepaid cards                                                | 0.055 (0.081)    | −0.054 (0.049)   | 0.712* (0.337)   |
| Advertising bans                                             | 0.034 (0.072)    | −0.009 (0.041)   | 0.343 (0.199)    |
| Class membership model [reference class 3]                          | Class 1 b (se) | Class 2 b (se) | Class 3 b (se) |
|-------------------------------------------------------------------|----------------|----------------|----------------|
| Age                                                              | −0.014* (0.007) | −0.014* (0.006) | [ref]          |
| Gender male                                                       | 0.055 (0.207)  | −0.300 (0.184) | [ref]          |
| Overweight (BMI 25–30)                                           | 0.032 (0.240)  | 0.518* (0.214) | [ref]          |
| Obese (BMI 30+)                                                  | 0.075 (0.304)  | 0.778** (0.271) | [ref]          |
| Self-assessed health poor or fair                                | 1.653 (1.112)  | 1.678 (1.062)  | [ref]          |
| Unsatisfied with own weight                                      | 0.720** (0.263) | 0.786*** (0.235) | [ref]          |
| Household income ($AU, 000s)                                     | −0.002 (0.002)  | −0.001 (0.002)  | [ref]          |
| At least one child living at home                                | −0.252 (0.207)  | −0.323 (0.185)  | [ref]          |
| Believes government has at least some responsibility for obesity in adults | 0.895** (0.336) | 1.494*** (0.325) | [ref]          |
| Believes government has at least some responsibility for obesity in children | 0.204 (0.337)  | 0.671* (0.321)  | [ref]          |
| Constant                                                          | 0.490 (0.611)  | −0.073 (0.572)  | [ref]          |

Class shares: 37% 40% 22%

Note: Class 1: Motivated. Class 2: Most likely to benefit. Class 3: Least likely to benefit. Survey block dummy variables were included in the class membership model to account for possible effects of blocks but excluded from the table in the interests of brevity.

The base levels for the attributes were: policy – mass media campaign, cost – zero extra tax per month, and effectiveness – no change in projected obesity rates (32% in 2020). No coefficients are reported for class 3 because the coefficients in the class membership model are relative to the reference class, which is class 3.

***p<0.001, **p<0.01, and *p<0.05.
combined were predicted to make up 37% of the policies most likely to be chosen based on the weighted average of class shares (43% in class 1, 46% in class 2, and 8% in class 3), while those with an underlying behavioral economic framework were predicted to make up 41% (46% in class 1, 52% in class 2, and 11% in class 3). The remaining 22% were predicted to choose no new policy (10% in class 1, 1% in class 2, and 80% in class 3).

Consistent with the underlying latent class results, the willingness to pay estimates (presented in Appendix 7) show those most likely to benefit (class 2) are willing to pay additional taxes for each of the policies except prepaid cards, while those least likely to benefit (class 3) are not willing to pay extra tax for any of the policies. Class 1 (motivated) have positive willingness to pay for all policies except prepaid cards, although the only policy for which this is statistically significant is the mass media campaign.

### TABLE 4 Predicted percentage of taxpayers who would choose each policy as best if offered all policies

| Policy                                      | Underlying economic framework | Cost ($/mo/taxpayer) | % point reduction in obesity | Predicted share of choices (%) | Latent class model |
|---------------------------------------------|-------------------------------|----------------------|-----------------------------|--------------------------------|------------------|
| Policies result in 1% point reduction in obesity prevalence |                               |                      |                             |                                |                  |
| No policy                                   | -                             | 0                    | 0                           | 22.2%                          | 10.1%            |
| Traffic lights                              | Standard                      | $0.035               | 1%                          | 17.7%                          | 16.8%            |
| Advertising bans                            | Budge                         | $0.035               | 1%                          | 11.1%                          | 11.0%            |
| Improve food quality in public institutions  | Budge                         | $0.033               | 1%                          | 10.6%                          | 13.9%            |
| Mass media campaign                         | Standard                      | $0.11                | 1%                          | 10.2%                          | 14.4%            |
| Fund physical activity infrastructure       | Nudge (broader)               | $5.00                | 1%                          | 9.6%                           | 9.1%             |
| Tax sugar-sweetened beverages               | Standard                      | 0                    | 1%                          | 8.8%                           | 11.7%            |
| Prepaid cards                               | Nudge                         | 0                    | 1%                          | 4.9%                           | 7.1%             |
| Financial incentives to exercise            | Nudge                         | $13.76               | 1%                          | 4.7%                           | 5.8%             |
| Policies result in 4% point reduction in obesity prevalence |                               |                      |                             |                                |                  |
| No policy                                   | -                             | 0                    | 0                           | 20.0%                          | 4.4%             |
| Traffic lights                              | Standard                      | $0.035               | 4%                          | 18.2%                          | 17.9%            |
| Improve food quality in public institutions  | Budge                         | $0.035               | 4%                          | 10.8%                          | 14.8%            |
| Advertising bans                            | Budge                         | $0.033               | 4%                          | 11.2%                          | 11.7%            |
| Mass media campaign                         | Standard                      | $0.11                | 4%                          | 10.3%                          | 15.4%            |
| Fund physical activity infrastructure       | Nudge (broader)               | $5.00                | 4%                          | 9.7%                           | 9.7%             |
| Tax sugar-sweetened beverages               | Standard                      | 0                    | 4%                          | 9.5%                           | 12.5%            |
| Prepaid cards                               | Nudge                         | 0                    | 4%                          | 5.3%                           | 7.6%             |
| Financial incentives to exercise            | Nudge                         | $13.76               | 4%                          | 4.8%                           | 6.1%             |

Note: Only statistically significant interaction terms used for prediction. Class shares: Class 1 (Motivated) = 37%, Class 2 (Most likely to benefit) = 40%, Class 3 (Least likely to benefit) = 22%. Policies are listed in order of the full sample predictions.

For detail on how costs were estimated.

Full sample predictions are a sum of the three class predictions weighted by the class shares.

***p<0.001, **p<0.01, and *p<0.05.

4 | DISCUSSION

Obesity is one of the greatest public health challenges of this century. As obesity rates continue to rise, new insights into reasons for that rise and policies designed to stem this rise are urgently needed. The public’s preferences concerning which policies they do or do not find acceptable are important, not least because as taxpayers they are also funders of
such policy. In addition, social acceptability is important, even when tax implications are low, because the response to, uptake of and ultimately the effectiveness of such policies often depends on such preferences. We have sought to add to the evidence base by exploring the preferences of taxpayers across eight policy options, accounting for the effectiveness and cost of such policies. Importantly, we explored preferences across a range of policies, including those inspired by both standard and behavioral economics. Policymaking considers a range of factors, such as effectiveness, cost-effectiveness, feasibility, inequality impacts. Our findings on social acceptability of these policies form part of the evidence base to inform such policymaking.

We found evidence of taxpayer support for funding of obesity prevention/reduction policies through increased taxation. Overall, 78% of the sample were predicted to choose a new policy as the best option at realistic levels of increased taxation and with a small projected benefit in reduced obesity. There were large differences across latent classes that could relate to personal capacity to benefit. While only one-fifth (19%) of class 3 (those least likely to benefit due to weight, desire for weight loss, and age) were predicted to choose a new policy, this contrasted with 99% in class 2 (those most likely to benefit). The finding of strong support for new policies even with small reductions in obesity might suggest that public sentiment is in favor of ‘doing something’ even in the absence of strong evidence of efficacy. It could also be that these are desired policies for reasons in addition to their impact on obesity, such as general health and wellbeing, dental health, mental health, or even social benefits such as recreation or community. In addition to benefits from the policies beyond a reduction in the obesity rate, such policies could also impact different parts of the population differently – for example, some policies may be of greater benefit to those in worse health and socioeconomic position. The impact that such broadening of the description of benefits would have on social acceptability of such policies could fruitfully be explored in further research.

Although previous research has generally not used a DCE approach or examined the same set of policies, it offers useful points of comparisons. Our findings that traffic light nutritional labeling and bans on advertising junk food to children were among the most preferred policies in this Australian sample (ranked first and second) concur with results from European surveys of agreement with different policy statements that found these to be among the most highly endorsed policies (Jürkenbeck et al., 2020; Mazzocchi et al., 2015). Food labeling also received strong support in a previous experimental study (Gendall et al., 2015) in New Zealand, which also found support for improving access to physical activity infrastructure and improvements to nutritional quality of food in schools, workplaces, and hospitals (ranked fifth and third respectively in our study). Unlike a DCE examining preferences for financial incentives in the UK (Promberger et al., 2012), which found that acceptability of incentives for weight loss increased with stated effectiveness of the incentive, we found no significant interaction between the incentive policy and effectiveness. Consistent with previous findings that beliefs about responsibility for obesity influence acceptability of obesity policies (Lund et al., 2011), we found such beliefs to predict the preference class to which individuals belonged.

Due to the widespread interest in obesity policies that are inspired by behavioral economics (and an interest in behavioral economic inspired public policy more broadly), we classified policies as having an underlying economic framework that was consistent with either (1) standard economics or behavioral economics to explore social acceptability of each. Within behaviorally informed policies we further classified policies as fitting within (2a) ‘nudge’ if they were about altering the direct choice environment of consumers to counteract behavioral biases in favor of healthier choices, or within (2b) ‘budge’ if they used regulation of providers to reduce the capacity for these behavioral biases to be exploited for commercial profit. The two least popular policies were classified as nudges: prepaid cards and payment incentives for exercise. The most popular policy (provision of information via traffic light food labeling) is consistent with a standard economic framework, while the two next most popular policies (bans on advertising to children and improving food quality in public institutions) have an underlying budge-type framework and demonstrate social support for regulatory approaches. The most popular nudge-type policy, improving the built environment to make physical activity an easy option, had a wider set of potential benefits beyond obesity reduction. It is interesting to note that mass media campaigns, which is perhaps the one policy which Governments have more readily supported, is not particularly popular. Similarly, and particularly relevant given this type of policy has been implemented in several settings (World Cancer Research Fund International, 2018), a 20% tax on sugar sweetened beverages was one of the least preferred policy options. Our results show that there is strong social support for regulatory approaches in the form of budge-type policies, noting that if traffic light labeling is viewed as a type of budge, then the three most popular policies would be budes.

We have classified each policy as stemming from one of these underlying economic frameworks, but this may be an artificial distinction in some cases. For example, paying individuals to participate in exercise can be seen as behavioral (overcoming present bias by bringing benefits into the present in terms of money) or it could be derived from standard economic theory as relating to a change in costs and benefits of exercise (the inverse of taxation on unhealthy behaviors).
Traffic light labeling can be classified as having standard economic underpinnings with a focus on making individuals informed decision makers, but it could also fit within a budge framework: regulating to constrain the ability of the food industry to market their products in ways that exploit behavioral biases, more in line with plain packaging regulations for smoking. The policies may also be seen through a number of other lenses; most prominent in the obesity literature would be a public health perspective which could classify them as preventive, targeted, or treatment, or according to the group in focus (population-level, individual). Public preferences may reflect the target group seen to benefit most, such as the focus on children in advertising bans, or whether they are perceived to have a financial impact on individuals (e.g., taxation on sugar sweetened beverages). The inference of preferences for policies derived from standard and behavioral economic theories was implicit as we did not highlight this in presenting the alternatives to participants. Familiarity with policy types may also have played a part, with the two least popular policies of prepaid cards and payment incentives being perhaps the least familiar to participants.

From a methods point of view, we note that the predictions are relative to the base policy of mass media campaigns. Our choice of mass media campaigns as the base for the probability analysis was because it is a commonly enacted policy. Changing the base would not impact the ranking in preference order across the eight policies. While we included eight policies, which is a large number in terms of levels for an attribute in a DCE, there are other obesity policies not included in this study, such as bariatric surgery, targeted at subsets of the obese population which have been shown to be effective at reducing obesity (Colquitt et al., 2014). We surveyed only taxpayers as the focus here was on the acceptability of tax-funded policies (this also ensured that the payment vehicle was relevant to all respondents). However, non-taxpayers vote alongside taxpayers so it would be relevant to also ascertain the acceptability of such policies to this group.

5 | CONCLUSION

Given the complex, inter-related nature of nutrition, physical activity, environment, and obesity, there is undoubtedly the need for a multi-faceted policy approach. This study has provided evidence regarding which policies would be considered more and less socially acceptable for inclusion in such an approach. There are a number of key policy messages from this study. Our results show that there is public support for obesity reduction and prevention policies and a willingness to fund this through taxation. Along with economic rationales for government intervention to address market failures, with imperfect information, negative externalities, and time-inconsistent preferences contributing to obesity, our findings could strengthen the argument for implementation of regulatory policies. In the Australian context of this study, the emphasis in obesity policy has been on approaches that do not restrict individual freedoms and avoid regulation (Farrell et al., 2016). Our results suggest that a shift toward regulation would be in line with public preferences. This also meets a request by policy makers for evidence regarding community support for regulation (Chung et al., 2012).

We also offer insight into relative social acceptability of behavioral versus standard economic inspired policies. There has been much interest internationally among public policy makers in nudge-based policies, which may be in part because it avoids the need for legislation and gives the state a smaller, less visible role in shaping behavior (Marteau et al., 2011; Schubert, 2017). Our findings that the two nudge-based policies were ranked last suggest that the general public is less enthusiastic and find nudge-based policy less socially acceptable. Such findings may prove relevant to the broader question of the appropriate place of behaviorally inspired policies in the public policy maker’s tool kit.

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CONFLICT OF INTEREST

The authors have no conflict of interest to declare.

ETHICS STATEMENT

The study was approved by the Monash University Human Research Ethics Committee.
DATA AVAILABILITY STATEMENT
The data that support the findings of this study are available from the corresponding author upon reasonable request.

ORCID
Jemimah Ride https://orcid.org/0000-0002-1820-5499
Nicole Black https://orcid.org/0000-0002-6396-7054

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