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RESEARCH PAPER

INCORPORATING LIFE SATISFACTION IN DISCRETE CHOICE EXPERIMENTS TO ESTIMATE WELLBEING VALUES FOR NON-MARKET GOODS

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Abstract

Subjective wellbeing (SWB) data have taken increasing prominence in economic research. The wellbeing valuation method uses measures of SWB, specifically life satisfaction, to value non-market goods by estimating the marginal rate of substitution between the non-market good and income. In order to measure values accurately, we need robust causal estimates of the impact of the non-market good and income on life satisfaction but this is difficult in observational data due to measurement error and endogeneity bias. This study uses a novel discrete choice experiment which incorporates life satisfaction to measure the impact of different life attributes, such as income and employment, on life satisfaction. We call this the Life Satisfaction Discrete Choice Experiment (LS-DCE). Through random assignment of life attributes in the LS-DCE we can estimate causal effects of the attributes on life satisfaction. The LS-DCE makes two contributions to the wellbeing valuation literature. Firstly, using the coefficients from the LS-DCE model we can estimate marginal rates of substitution between income and any other life attribute which allows us to estimate values for non-market goods directly in the LS-DCE. Secondly, the results of the LS-DCE can be used to estimate the causal effect of income on life satisfaction which can be used in wellbeing valuation more generally.

Keywords: wellbeing; income; non-market valuation; wellbeing valuation
JEL codes: I30; I31;

1. Introduction

Interest in subjective wellbeing (SWB) data has grown rapidly in economics (MacKerron, 2011) and one prominent use of SWB data has been for the purpose of valuing non-market goods using the Wellbeing Valuation (WV) approach. The premise of the WV method is to estimate compensating and equivalent measures of welfare change from data on people's SWB. As Fujiwara and Dolan (2016) report SWB is typically measured as life satisfaction in WV studies. This is achieved by calculating the marginal rate of substitution (MRS) between the non-market good and income to hold SWB constant. In order to do so, we need to understand the causal effect of the non-market good (Q) and income (M) on life satisfaction. Denoting the effect of a variable on life satisfaction with β, in its most basic form the MRS is simply the ratio of impacts:

(1) $$MRS = -\frac{\beta_Q}{\beta_M}$$

Usually in the WV literature equation (1) is estimated using coefficients from multivariate regression analysis. However, estimating unbiased causal effects of Q and M using such methods is difficult due to measurement error (especially problematic for income), selection bias, and the potential for reverse causality. Random assignment of the variables of interest such as income is unlikely to be a viable option in many cases, and when using observational data such as national survey data it is difficult to find natural exogeneity in the variables of interest. Understanding the causal relationship has been especially problematic for income in the wellbeing literature, which makes it difficult to measure values robustly using the WV approach (Fujiwara and Dolan, 2016).

A number of studies have attempted to address these issues by using instrumental variables for income and other variables (e.g., Powdthavee, 2010; Knight et al., 2009; Levinson, 2012). However it has proven difficult to find instruments for income that are exogenous and the exclusion restriction assumption rarely holds (Fujiwara, 2013). Lottery wins data seem to offer the best solution for instrumental variable analysis (Lindahl, 2005; Fujiwara and Dolan, 2016), but there are questions surrounding the external validity of these studies and data in the UK on lottery wins is now quite dated, coming from the British Household Panel Survey (BHPS) from 1997 to 2009 (Fujiwara, 2013).

In this paper we take a novel approach to estimating the relationship between life satisfaction and variables of interest (including income) using a discrete choice experiment (DCE) whereby respondents are asked to make choices over different hypothetical lives which differ in terms of a number of attributes such as health, employment and income. Respondents choose which life has the highest life satisfaction. We call this the Life Satisfaction Discrete Choice Experiment (LS-DCE) approach. The advantage of a DCE approach is that we can randomly assign changes in the life attributes holding all else constant which means that we can understand the causal effect of changes in the life attributes, such as employment and income, on wellbeing providing robust measures of value using the WV method.

In this respect our study follows in the path of a small number of studies in the wellbeing literature that have started to use choices (effectively, stated preferences) over different hypothetical lives or life histories to better understand what drives wellbeing (e.g. Adler et al., 2017; Benjamin et al., 2014). We use our LS-DCE study in two novel ways to improve valuations of non-market goods using SWB data. Firstly, we use the results to estimate marginal rates of substitution between income and life attributes such as health and employment holding life satisfaction constant. This allows us to estimate values for these life attributes using robust causal estimates. Through this we have developed a new approach to measuring non-market values using SWB data by integrating life satisfaction metrics into a DCE. Secondly, we use the results from the LS-DCE study to estimate the causal effect of income on life satisfaction. This estimate can be used in the WV approach more generally to derive robust values as it provides an estimate of β_M in equation (1).

Section 2 sets out previous related literature focussing on studies that have used stated preference and choice surveys to elicit data about SWB and wellbeing. Section 3 sets out the data, sampling method, DCE survey and methodology for the analysis. Section 4 presents the results and Section 5 concludes.

2. Literature review

The literature on the relationship between income and life satisfaction is substantial and is summarised in Fujiwara (2013) and Fujiwara and Dolan (2016). The majority of studies have relied on multivariate regression analysis, which as discussed above, is fraught with problems due to measurement error and endogeneity bias. A number of instrumental variable studies exist, but the validity of the instrument is often questionable (Fujiwara, 2013), with lottery wins instruments likely to provide the best option or solution.

Our study uses a stated preference framework under a DCE to elicit preferences for different life histories in order to understand the effect of income and other life attributes on life satisfaction. This study therefore follows in a different tradition to the regression and instrumental variables studies mentioned above. We are aware of a handful of previous studies that have employed stated preference techniques in wellbeing analysis. Benjamin et al. (2012) ask people to choose their preferred life based on attributes such as salary and amount of sleep and also asked them to rate their level of life satisfaction for each life, finding a strong correlation between choice and life satisfaction.

Benjamin et al. (2014) develop a wellbeing index including measures of SWB, health, relationships, security and resources and respondents are asked to choose among two options differentiated by these factors. These responses are used to calculate marginal utilities for each of the factors and the authors find that measures of SWB and health have relatively large marginal utilities, as do family-related aspects, security, values of morality and meaning, freedom of choice and resources.

Adler et al. (2017) ask respondents to make a pairwise ranking of two possible lives: one life is described as higher in some aspect of SWB, but lower in some non-SWB dimension; and vice-versa for the second life. Therefore, the level of SWB is directly incorporated in the life described, which is different to Benjamin et al (2012) who ask respondents to choose the best life and rate the lives in terms of SWB. The non-SWB dimensions include income, physical health, family, career success, and education. For example, the respondent might be asked to choose between a life characterised by a high level of happiness and poor physical health, and one characterised by a lower level of happiness and better physical health. These choices are used to estimate marginal effects of each SWB and non-SWB dimension on choice, allowing the authors to assess to what extent SWB and non-SWB factors matter to people's lives.

Our study is different but borrows some aspects from these previous studies. Unlike Benjamin et al. (2014) and Adler et al. (2017) we do not assume that SWB is a determinant in the utility function. These authors are interested in the relative importance of measures of SWB like life satisfaction and other life attributes such as income, health and education. However, in our study, SWB is the objective function itself as we want to assess the impact of different life attributes such as income and employment on life satisfaction. Our study therefore has more similarities with Benjamin et al. (2012) in this respect. However, in a similar approach to Adler et al. (2017) we use vignettes to describe different lives which we prefer as it means we do not need to ask respondents to think about changes to their own lives which may not be realistic.

Our study adds to the literature in three important ways. First, we use the DCE and stated choices to assess how life attributes impact on life satisfaction. Second, from this we are able to derive values for different life attributes based on the marginal rates of substitution between the life attribute and income. And third, we estimate the causal effect of income on life satisfaction, a key issue in wellbeing research. Using this estimate it is possible to derive more robust values in the wellbeing valuation approach. Our study, thus, provides a new approach for valuing non-market goods using life satisfaction data in a DCE.

3. Data and methodology

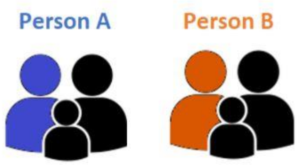
3.1. Life satisfaction discrete choice experiment (LS-DCE) survey

We developed a DCE survey whereby we presented respondents with a series of two different hypothetical lives in a choice card and we asked respondents to choose which of two people they thought had higher life satisfaction based on life characteristics. It was stated that the two people were of the same age, gender, and family make-up and were living in the same area, but that they had different levels of income, health, employment status and social relationships. Below is an example of the question that respondents were asked to reply to.

Figure 1. Example choice card from the LS-DCE survey

We will now present you with information about **Person A** and **Person B**.

Both are 30 years of age, female, have a spouse, one child and live in the suburbs in Northern England. There is no difference between them other than the ones listed.



You will be asked to answer **10 choice tasks** in which you need to choose **which person you feel would be more satisfied with their life**, where 'life satisfaction' is defined on a scale of **0 to 10**, 0 being '**not at all satisfied**' and 10 being '**completely satisfied**'. Once you have made your choice between Person A and Person B, we will ask you to **provide a number from 0 to 10** for both, reflecting the **level of life satisfaction** you think each person would have. You will then be able to move on to the next choice task.

Remember: **apart from the characteristics described in the questions, the two people are equal in all other respects!** So please base your choices **exclusively** on the characteristics given.

	Person A	Person B
General health	Poor	Good
Current Annual Household income	£20,000	£15,000
Employment status	Unemployed	Employed
Can rely on family or friends	Not at all	A lot

Person A

Person B

The characteristics by which each person will be described are defined in the table below.

Characteristic	Definition
General health	This is an individual's general health and can be 'poor', 'fair', 'good', 'very good' or 'excellent'.
Household income	This is the current annual income of a household. It includes all possible sources of income, including the salary of all household members, social welfare payments, pensions, interest from savings, income from owning properties etc.
Unemployment	This refers to whether an individual is unemployed, meaning that they are out of work and actively seeking employment. This does not necessarily mean that the individual has no other source of household income.
Can rely on family or friends	This refers to how much an individual can rely on their family or friends in case he or she has a serious problem. Possible answers are 'not at all', 'a little / somewhat' or 'a lot'.

Respondents were presented with 10 binary choices over two different hypothetical people with the life characteristics randomised and different for each choice. The survey also included a series of standard sociodemographic questions about the respondent. Randomly assigning levels in the life attributes meant that we could control for all other drivers of a person's life satisfaction which allows us to tease out the causal effect of each attribute on life satisfaction.

The key difference between this LS-DCE and other more standard DCEs is the definition of the latent variable. In DCEs people usually choose their preferred option based on a set of attributes about the good or service (e.g., a car or a new home). Choice is therefore based on preference, which is the standard or underlying measure of welfare in economics (known as utility). Since the focus of this study is on life satisfaction, we explicitly set the latent (or choice) variable as life satisfaction. That is people do not choose which life they prefer, but rather they choose which life they think would create the highest level of life satisfaction out of the two choices[1] . This allows us to estimate the impact of variables like income on life satisfaction rather than on preference utility.

3.2. Sample

The survey was conducted online using the online data panel provider Toluna. We collected 301 responses from people aged 16+ in the UK on 23 October 2019. Nineteen responses were dropped from the analysis for a variety of reasons such as illogical responses or completing the survey too quickly to have feasibly read the questions. This left 282 legitimate respondents as the final sample size. This generated 2,820 separate choices in our data since each respondent made 10 different binary choices. Quotas on age, gender, income and region in the UK were set to make the sample nationally representative.

3.3. Analysis

Given the total of 2,820 choices, let each choice be denoted by $k = 1,2, \ldots 2,810$. When making the choice between Person A and B, respondents did so based on who they thought had the higher level of life satisfaction and, therefore, they considered the difference in life satisfaction between the two individuals. Let $LS_k = LS_{A,k} - LS_{B,k}$ represent the latent choice variable capturing the difference in life satisfaction (LS) between the

[1] In theory the life the respondents prefer could be different to the life they think has the highest life satisfaction although this is unlikely given the strong relationship between life satisfaction and choice (Frijters, 2010).

two individuals in the options. The respondent will choose person i when $LS_{i,k} > LS_{-i,k}$. We assume that the level of life satisfaction perceived by the respondent for each person in the choice is a function of the characteristics (health, employment, social relations, and income) describing the individuals presented in the choice questions such that:

(2) $LS_{i,k} = \theta + \beta_{HF}HF_{i,k} + \beta_{HG}HG_{i,k} + \beta_{HVG}HVG_{i,k} + \beta_{HE}HE_{i,k} + \beta_{E}Emp_{i,k} + \beta_{\ln(M)}\ln\left(M_{i,k}\right) + \beta_{SM}SM_{i,k} + \beta_{SH}SH_{i,k} + \varepsilon_{i,k}$

Where:

- $i = A \; or \; B$ indicating which hypothetical person in choice k is being considered.
- θ is a constant.
- $HF_{j,k}$ is a dummy variable equal to 1 if person j has Fair health in choice k
- $HG_{j,k}$ is a dummy variable equal to 1 if person j has Good health in choice k
- $HVG_{j,k}$ is a dummy variable equal to 1 if person j has Very good health in choice k
- $HE_{j,k}$ is a dummy variable equal to 1 if person j has Excellent health in choice k
- $Emp_{j,k}$ is a dummy variable equal to 1 if person j is employed in choice k
- $SM_{j,k}$ is a dummy variable equal to 1 if person j is rated as “Somewhat/A little” for social relations in choice k
- $SH_{j,k}$ is a dummy variable equal to 1 if person j is rated as “A lot” for social relations in choice k
- $M_{j,k}$ is the income of person j in choice k
- $\varepsilon_{j,k}$ is the random error term assumed to be normally distributed

We analysed respondents’ choices between Person A and B using a probit regression model. This allows us to estimate the coefficients on any of the variables in equation (2) (denoted as β_Q here) up to a scaling transformation. The coefficients estimated from (2) do not denote the absolute impact of the variable on the level of life satisfaction because we only observe *differences* in the level of life satisfaction (through the respondents’ choices) and this is one form of scaling. Furthermore, there may be additional scaling present because the impacts of the variables on life satisfaction have been predicted by the respondents for the vignettes rather than actually experienced by individuals.

3.3.1. Estimating values from the LS-DCE

We estimate values for all of the life attributes by calculating the marginal rate of substitution (MRS) between the life attribute and income by taking the ratio of the coefficients from the probit model estimate of equation (2):

(3) $MRS = -\frac{\beta_Q}{\beta_M} = -\frac{dLS}{dQ}\frac{d\ln(M)}{dLS}\frac{dM}{d\ln(M)} = -\frac{\beta_Q}{\beta_{\ln(M)}} * M$

Where M is individual income (approximated by average household income divided by average household size in the UK).

Note that the issue of scaling mentioned in section 3.3. is not relevant for when we want to estimate ratios between coefficients as the scaling factor drops out of the formula in equation (3). Equation (3) allows us to value the life attributes (e.g., health and employment) directly using the results from the probit model and without having to adjust for scaling.

The accurate estimation of values using LS-DCE relies on a number of assumptions. Respondents need to be able to accurately assess how differences in life attributes impact on life satisfaction and to make the correct choice each time based on this information. It is also assumes that the information given to the respondents about the hypothetical persons is enough to make a choice. We focussed on four life attributes in this study and values may change depending on the life attributes presented. For example, presenting information about education may modify the relative importance that people place on other life attributes such as income.

3.3.2. Estimating the causal effect of income on life satisfaction

To estimate the impact of income on life satisfaction requires further analysis to address the scaling factor discussed above. There are two issues related to the scaling factor. The first is that the coefficients in (2) represent the impact on choice between individuals rather than on life satisfaction of the individuals themselves. We therefore only know an ordinal ranking of life satisfaction from the choices and we need to convert this on to a scale, which here will be a 1 to 7 scale for life satisfaction to align with previous research. We denote this as an unknown constant (γ). Second, how a survey respondent judges someone else's life satisfaction based on certain variables such as employment and income (predicted life satisfaction, LS_P) may be different to how those variables actually affect people's own ratings of their life satisfaction (experienced life satisfaction, LS_E). That is, the effect of a good on predicted life satisfaction needs to be scaled (by a factor denoted δ) to calculate its effect on experienced life satisfaction:

(4) $$\frac{dLS_P}{dQ} = \delta_Q * \frac{dLS_E}{dQ} = \delta_Q * \beta_Q$$

To adjust our maximum likelihood estimators from the probit model for the income coefficient to account for these two scaling factors we assume that δ is constant across all variables and γ is constant by construction. Therefore, differences between respondents' predicted effect of a variable (Q) on life satisfaction and the actual effect of Q on someone's life satisfaction is the same magnitude or proportion across all types of variables. Therefore, our maximum likelihood estimators from the probit estimation of equation (2) represent:

(5) $$\beta_{MLE,Q} = \gamma * \delta * \beta_Q$$

To estimate an income coefficient (and indeed a coefficient for any of the variables in (2)), we need to estimate $\gamma * \delta$ and rearrange equation (5) as follows (substituting M for Q):

(6) $$\beta_M = \frac{\beta_{MLE,M}}{(\gamma * \delta)}$$

To do so, we compare coefficients for one of the variables in (2) with a robust coefficient for the same variable from analysis that looks at the actual experienced effect of the variable on life satisfaction. To achieve this, we require an unbiased estimate of at least one of the variables in (2). We use Fujiwara's (2013) estimate of the effect of employment on life satisfaction, which is a robust estimate of the impact of employment as it is based on exogenous redundancies to measure employment status. We estimate $\gamma * \delta$, by taking the ratio of the maximum likelihood estimator for employment from our survey analysis to the coefficient for employment from Fujiwara (2013):

(7) $$\gamma * \delta = \frac{\beta_{MLE,E}}{\beta_E}$$

Assuming this estimate for β_E is unbiased this will give unbiased estimates of the scaling factor $\gamma * \delta$. Finally, we use the results from equation (7) in equation (6) to give a *true* income coefficient.

Caveats to note regarding this analysis are the assumptions we make about the constant scaling factors, which should be tested in future research. The assumptions set out in section 3.3.1. regarding people's ability to make choices are also relevant.

4. Results

4.1. Values for different life attributes from the LS-DCE

Table 1 shows the results from the probit estimation of equation (2). All variable coefficients were significant at the 1% level.

Table 1. Probit regression results

	Coefficient	Robust standard error
Health: Fair	0.241***	0.0789
Health: Good	0.555***	0.0630
Health: Very Good	0.832***	0.0948
Health: Excellent	0.595***	0.0668
Employment	0.184***	0.0321
Log (household income)	0.510***	0.0360
Social relations: Somewhat / A little	0.256***	0.0473
Social relations: A lot	0.385***	0.0453
Constant	0.0616**	0.0336
Number of observations	2,820	
Pseudo R-squared	0.1228	

*Notes: *** Significant at < 1%, ** significant at < 5%, * significant at < 10%. Reference group for health is 'Poor' health. Reference group for social relations is 'not at all'.*

Table 2 sets out values for each variable based on the MRS with income from the probit model based on estimating equation (3) [2] (we use a median income of £30,800 and average household size of 2.4 which equates to a value for M of £12,833).

Table 2. Wellbeing values for life attributes from the LS-DCE results

Variable	Relative coefficient (all coefficients divided by $\beta_{\ln(M)}$)	Value
Health: Fair	$\beta_{HF} = 0.47$	£6,032
Health: Good	$\beta_{HG} = 1.09$	£13,988
Health: Very Good	$\beta_{HVG} = 1.63$	£20,918
Health: Excellent	$\beta_{HE} = 1.17$	£15,015
Employment	$\beta_{E} = 0.36$	£4,620
Social relations: Somewhat /A little	$\beta_{SM} = 0.50$	£6,417
Social relations: A lot	$\beta_{SH} = 0.75$	£9,625

Notes: Values are estimated by multiplying the relative coefficient by £12,833 as per equation (3).

This demonstrates how a DCE study can be used in a novel way to estimate values for non-market goods using life satisfaction as the outcome. These represent robust values since the coefficients in Table 1 can be assumed to be unbiased estimates due to the randomisation of the life attributes in the DCE. A value for any type of life

[2] Note: for sensitivity analysis we also conducted the same analysis with a logit model and found the ratios (and values) to be very similar.

attribute can be estimated in this way by introducing the attribute (e.g., crime or pollution) into a similar LS-DCE study.

The question then becomes why we would estimate values in this way using an LS-DCE rather than ask people for their willingness to pay values directly for these attributes. The reason is that stated preference methods like contingent valuation are difficult to apply to value life attributes like health, employment and social relationships because establishing a hypothetical market for them would be difficult and respondents struggle from an ethical perspective with putting a value on things like health. One of the key advantages of the WV method is that it can be used to value life attributes and states of the world like health and employment since people are not asked to directly place a willingness to pay value on these things. The problem, however, in WV has been estimating causal effects of life attributes on life satisfaction. Subject to the assumptions and caveats stated above, the LS-DCE solves for these issues to provide a robust way of valuing these types of life attributes and outcomes which have been inherently difficult to value using other valuation methods.

The LS-DCE approach to WV, however, requires a new LS-DCE survey to be developed and administered each time a new life attribute or non-market good is to be valued. An alternative way of using the LS-DCE results is to develop an estimate of the causal effect of income on life satisfaction which can be used in equation (2) in scenarios where we already have a robust estimate of the causal effect of the variable being valued. For example, if we have a robust estimate of the impact on life satisfaction of, say, living in a polluted area we can use that estimate as β_Q in equation (2) paired with an estimate of the causal effect of income for β_M. Estimating the causal effect of income therefore provides a second way in which the LS-DCE results can be used in WV to value life attributes and non-market goods more generally.

4.2. The causal effect of income on life satisfaction using the LS-DCE

We first need to estimate the scaling factor $\gamma * \delta$ from equation (7). Using Fujiwara's (2013) estimate of the causal effect of employment on life satisfaction (0.436) we calculate the scaling factor as follows using the coefficient from the probit model for employment:

(7) $$\gamma * \delta = \frac{\beta_{MLE,E}}{\beta_E} = \frac{0.184}{0.436} = 0.422$$

Substituting equation (7) into equation (6) we can estimate the income coefficient as:

(6) $$\frac{\beta_{MLE,M}}{(\gamma * \delta)} = \frac{0.510}{0.422} = \beta_M = 1.21$$

This states that the impact of log of household income on life satisfaction is 1.21. However, we need to make one final correction as the expectation of the inverse of a random variable is not equal to the inverse of its expectation. In order to correct for this, we used Monte Carlo simulations to generate a distribution for $\widehat{\beta_{MLE,E}} \sim N(0.184, 0.0321)$, $n = 500$; $\widehat{\beta_E} \sim N(0.436, 0.062)$, $n = 500$; and $\widehat{\beta_{MLE,M}} \sim N(0.510, 0.0360)$, $n = 500$. We used these distributions to calculate an unbiased estimate of β_M. With this method $\beta_M = 1.25$ with $\sigma_{\beta_M} = 0.0360$. This gives a 95% confidence interval of (0.75, 2.04). Repeated simulations gave similar results.

Note that this is calibrated on a 1 to 7 scale for life satisfaction as the employment coefficient from Fujiwara (2013) is on a 1 to 7 scale). This estimate is close to Fujiwara's (2013) estimate using lottery wins as exogenous income shocks in an instrumental variable framework which produced a coefficient of 1.103 for log of household income (on a 1-7 scale for life satisfaction). The result in this paper together with our previous research using lottery wins would therefore suggest that the causal effect of log point change in income on life satisfaction is between 1.1 to 1.25. The higher the coefficient for income the lower or more conservative will be the values that are derived from WV since the income coefficient is the denominator in the MRS equation (1).

How does this compare to coefficients for income from other studies in the literature? Although there is variation in how income is defined, the scale of the life satisfaction question and the functional form of the model across different studies, it is typical to find studies using observational data with non-exogenous changes in income reporting coefficients on log of household income of between 0.2 – 0.7 for life satisfaction on a 1 to 7 scale (e.g. Powdthavee, 2010; Kuehnle and Wunder, 2015; Howley, 2016; McDonald and Powdthavee, 2018), with an average of around 0.2. Therefore, our estimate of the impact of income is about six times higher which will lead to much more conservative value estimates in the WV methodology, addressing the often-cited issue in the WV literature that wellbeing values tend to be implausibly too high (e.g., Dolan and Metcalfe, 2008).

We now demonstrate how our estimate for β_M can be used to estimate values in the WV approach more generally (outside of the LS-DCE study). Since income is in logarithmic format the estimation process is a little more involved than equation (1) and is set out in Fujiwara and Dolan (2016) as follows:

(8) $$M - e^{\left[\ln(M) - \frac{\beta_Q}{\beta_M}\right]}$$

Using equation (8) we estimate the value of employment using 0.436 from Fujiwara (2013) as β_Q for employment, which as discussed above is a causal estimate, 1.25 for the impact of log of income on life satisfaction (β_M) and as set out in section 4.1., £12,833 for M. This produces a value of £3,779 for employment. This is quite similar to the value of £4,620 from the LS-DCE results in Table 2 demonstrating that both methods lead to similar results because they are based on causal estimates for employment and income. We can compare this value to the value we would derive if we used the average income coefficient size reported in the literature of 0.2 for β_M. This would give us a value for employment of £11,383, which is significantly higher due to the smaller income coefficient.

5. Conclusion

This paper uses a novel LS-DCE study to generate wellbeing values and to estimate the causal effect of income on life satisfaction. Random assignment of different life attributes in the LS-DCE permits estimation of the causal effect of income and other variables such as health and employment on life satisfaction. This is a significant advantage of the LS-DCE design given the difficulties in estimating causal relationships between SWB and other variables using observational data. However, the assumptions and caveats set out in this paper should be noted when using the results and in particular future research should assess the validity of our assumptions regarding the scaling factors.

The LS-DCE approach provides two options for valuing non-market goods using SWB data. First, an LS-DCE survey can be developed to value any kind of life attribute or non-market good using life satisfaction. For life attributes such as health and employment this is a significant advantage of the LS-DCE approach since these outcomes are difficult to value using other stated preference or revealed preference methods and they can be problematic to value using the more traditional WV method with observational data since it is hard to estimate causal relationships between life satisfaction and these variables. For other types of non-market goods, such as clean air, low rates of crime or education, the LS-DCE offers an alternative valuation method that could be used alongside methods like contingent valuation or hedonic pricing. The second option is that the LS-DCE has provided a new estimate for the causal effect of income on life satisfaction. If we have an estimate of the causal effect of the non-market good on life satisfaction from a separate study, we can use the income estimate from the LS-DCE to value non-market goods using the WV approach. In other words, the estimate of the causal effect of income from this LS-DCE study can be used as a substitute for the coefficient on income (β_M) in any WV study.

The LS-DCE method produces a coefficient for log of income that is significantly higher than studies based on observational data whereby life satisfaction is regressed on to individual income, but the effect size from the LS-DCE for income is in line with our previous study that uses exogenous changes in income due to lottery wins. This suggests that income coefficients estimated from observational studies, where income is not randomly assigned, are downward biased and that the true causal effect of income on life satisfaction is higher. This means that values for non-market goods will be lower when we use the (higher) unbiased estimate of the impact of income since the coefficient on income features in the denominator in the WV calculation. We can, therefore, produce more accurate values in WV based on this higher unbiased effect of income either within an LS-DCE itself or by using the income coefficient from the LS-DCE in this study. As we have shown here, both methods produce realistic values.

This study provides evidence that the coefficient on income is likely be higher than has been measured in regression analysis to date and produces similar findings to Fujiwara (2013), supporting the finding that the coefficient is higher than 1. This is substantially larger than the average coefficient size found in the literature of around 0.2. As this is the first time an LS-DCE has been used to estimate the impact of income on life satisfaction future research should test the assumptions we make in this study. Using a coefficient for log of household income of 1.25 in WV will lead to lower and more conservative values and hence there are arguments of using this coefficient in WV.

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