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A General Method for Valuing Non-Market Goods Using Wellbeing Data: Three-Stage Wellbeing Valuation

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Abstract
Subjective wellbeing data is becoming increasingly popular in economics research. The wellbeing valuation approach uses wellbeing data instead of data gleaned from preferences to attach monetary values to non-market goods. This method could be an important alternative to preference-based valuation methods such as contingent valuation, but there are a number of significant technical deficiencies with the current methodology. It is argued that the current method derives biased estimates of the value of non-market goods. The paper presents *Three-Stage Wellbeing Valuation*, a new approach to valuation using subjective wellbeing data that solves for the main technical problems and as a result derives estimates of welfare change and value that are consistent with welfare economic theory. As an example, I derive robust values associated with unemployment using the new approach and compare these to biased values derived from the standard wellbeing valuation method. Values derived from *Three-Stage Wellbeing Valuation* can be used in cost-benefit analysis.

JEL Classifications: C39; D6; D61; I31; J68
Keywords: subjective wellbeing; non-market valuation; cost-benefit analysis; unemployment; causal inference

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1. Introduction

The literature on subjective wellbeing (SWB) within economics is growing fast. Measures such as life satisfaction and happiness have increasingly been used as proxies for welfare; as complements or even alternatives to preference satisfaction accounts (B. S. Frey, Luechinger, & Stutzer, 2009; Bruno S. Frey & Stutzer, 2002; Stutzer & Frey, 2004; Stutzer & Frey, 2003; van den Berg & Ferrer-i-Carbonell, 2007). A potentially significant sub-field of this work has been the use of measures of SWB to derive monetary values for non-market goods. The Wellbeing Valuation (WV) approach uses SWB measures to derive marginal rates of substitution (MRS) between a non-market good and income, which can be used to measure compensating and equivalent surplus, standard measures of welfare change in and cost-benefit analysis (CBA). The approach, is an alternative method for valuing goods that does not rely on people's revealed or stated preferences and this is an important development in light of the growing evidence from behavioural economics, which suggests that preferences may not always be consistent and well-informed, raising questions about their reliability as indicators of welfare (see papers in Slovic & Lichtenstein, 2006).

This paper shows that, although a potentially very useful technique, the WV methodology applied thus far has provided biased estimates of the value of non-market goods due to a number of technical reasons and there are problems surrounding the interpretation of values derived using SWB. The main evidence of this has been the consistent finding of very large valuation estimates from WV. For example, Clark and Oswald (2002) estimated the cost of unemployment to be about £23,000 per month in addition to forgone wage income. Generally, we find that values estimated using WV tend to be magnitudes higher than those estimated using preference-based techniques (Dolan & Metcalfe, 2008). This has made it all but impossible to use this emerging methodology in CBA and public policy in a meaningful way. The main technical problems with the current WV methodology are that the statistical methods do not generally derive robust causal estimates and that marginal rates of substitution cannot be estimated from the single-equation econometric models that are employed.

The paper presents a new methodological framework for Wellbeing Valuation that provides robust measures of welfare change and monetary value that are consistent with welfare economic theory and that hence can be used in CBA. The major contribution is to move away from single-equation models to estimate separate models for income and the non-market good, which allows values to be estimated using experimental or observational data or even a combination of both. This method is called *Three- Stage Wellbeing Valuation* and I use it to estimate the costs of unemployment as an example. Under Three-Stage Wellbeing Valuation I find that the compensating surplus for unemployment is about £10,700 per year, or about £890 per month. This is a significant improvement on the extremely and implausibly high values for unemployment that one would derive using the current methodology and hence the new method should improve the standing of wellbeing valuation in academic research and policy-making.

The paper is set out as follows. In section 2 we start with a brief recap of the theory of value and in section 3 I show how this can be measured with SWB data and discuss the main problems associated with the current WV methodology. Section 4 sets out the new approach to WV: Three-Stage Wellbeing Valuation. I use an example estimating the costs associated with unemployment. Finally, sections 5 and 6 provide a discussion and conclusions.

2. The Theory of Value

In welfare economics the theory of value is expressed as the equivalent (ES) or compensating surplus (CS) of a good. CS is the amount of money, paid or received, that will leave the agent in his *initial* welfare position *following* a change in the good. ES is the amount of money, to be paid or received, that will leave the agent in his *subsequent* welfare position in *absence* of a change in the good[1]. This can be translated in terms of willingness to pay (WTP) or accept (WTA) as follows:

[1] Definitions from Bockstael and McConnell (1980).

Table 1. The relationship between ES, CS, WTP and WTA

	Compensating Surplus (CS)	Equivalent Surplus (ES)
Welfare gain	*WTP for the positive change*	*WTA to forego the positive change*
Welfare loss	*WTA the negative change*	*WTP to avoid the negative change*

ES and CS are calculated from the marginal rate of substitution (MRS) between money and the good. Although Hicks' pioneering work on the theory of value did not initially use a preference satisfaction account of welfare, customarily ES and CS are measured using revealed preference (RP) or through stated preference (SP) methods, such as contingent valuation. Preference-based valuation methods suffer from problems related to preference anomalies and survey biases like protest values, that have been well-documented in the past literature and are not discussed further here (see Fujiwara & Campbell, 2011 for detailed description of these problems). The WV approach in part has developed off the back of many of the critiques surrounding traditional preference methods. By measuring welfare in a different manner it has been suggested that many of the problems related to preference-based valuation methods can be overcome.

3. Measuring Value Through Wellbeing: The Wellbeing Valuation Approach

In the WV approach it is possible to estimate MRS directly since we have an "observable" measure of welfare. Here I derive estimators of welfare change with SWB data that are consistent with welfare economic theory. We will see that this is different to the theoretical approach used in the WV literature, hence why it has produced biased estimates of welfare change. Let us use compensating surplus as an example and define CS for a non-market good (Q) as:

$$v(p^0, Q^0, M^0) = v(p^1, Q^1, M^1 - CS) \quad (1)$$

where $v(.)$ is the *indirect utility function*, M is income and p are prices. Superscripts 0 and 1 respectively signify conditions before and after provision of the good Q, which here is assumed to affect prices and have a positive impact on utility. The main issue is that in non-market valuation we are interested in quantifying *all* of the changes in human welfare that accrue from a change in the provision of the good – what Bateman and his colleagues have called *total economic value* (TEV) (Pearce, Ozdemiroglu, & al., 2002). This means that we are interested in both the *direct* and *indirect* impacts of Q on welfare – for example, for an environmental programme that protects a large forest area, this would include the direct enjoyment I get out of using the area, any health or other benefits I may derive indirectly due to carbon dioxide sequestration.

In the WV approach we estimate the elements of equation (1) empirically by using a direct 'observable' measure of utility:

$$u(Q, M, X) \tag{2}$$

where X is a vector of other determinants of welfare (u). And this measure of utility is subjective wellbeing, such that:

$$SWB(Q, M, X) \tag{3}$$

where SWB is some metric of wellbeing such as life satisfaction and we assume $SWB = u$. We recognise possible relationships between Q and the other variables in (3) so that the TEV of Q can be estimated. Using (3) instead of the indirect utility function in (1) and solving for CS we get:

$$CS = (M^1 - M^0) + \frac{SWB'_X \cdot X'_Q(Q^1 - Q^0)}{SWB'_M} + \frac{SWB'_Q(Q^1 - Q^0)}{SWB'_M} \tag{4}$$

In words this states that: *Compensating Surplus = (impact of Q on M)*
+ (the MRS between income and the indirect effect of Q on SWB via X)
+ (the MRS between income and the direct effect of Q on SWB).

Naturally we must also acknowledge that M may impact on SWB indirectly in (4) and so SWB'_M should represent the total derivative for income. Indeed, the CS for a change in the non-market good (ΔQ) can be reformulated in terms of total derivatives:

$$CS = {-\frac{\mathrm{d}\,SWB}{\mathrm{d}\,Q} \cdot \Delta Q} \Big/ {\frac{\mathrm{d}\,SWB}{\mathrm{d}\,M}} \qquad (5)$$

Equation (5) will estimate the TEV of Q in line with welfare economic theory.
Two further conditions are that (a) the total derivatives in (5) must come from the same population group so that they are comparable. I will call this issue *sample matching*. Second, $\frac{\mathrm{d}\,SWB}{\mathrm{d}\,Q}$ should have a clear interpretation where there are heterogenous treatment effects, so that results are useful for policy.

When interpreting the results from WV, we should recognise that preference and mental state (ie, SWB) accounts of welfare differ markedly and hence there is no reason to believe that values derived from WV will or should (in a normative sense) align with neatly values from SP and RP methods. Furthermore, there some differences in the interpretation of the values. In WV we are *not* equating SWB with preferences: we are equating SWB with the notion of welfare. It is out of the scope of this paper to fully discuss the philosophical differences between these different accounts of welfare, but we should note that unless people satisfy preferences with the sole purpose of maximising life satisfaction (or whatever measure we use in the WV approach), then WV values and preference values will not align. In sum, *values derived using WV should not be seen as WTP or WTA amounts*. Instead, they are alternative measures of CS and ES as set out in welfare economic theory. The literature to date has tended to use the term 'income compensation' to label the values derived from WV. This is misleading because it relates strongly to the idea of WTA and that actual compensation could be made. Instead, I propose the term '*monetary equivalent value'* for the values derived from WV (regardless of whether they are CS or ES).

3.1 The Wellbeing Valuation approach: methodology to date and associated problems

The WV approach is an emerging method with approximately 60 publications over the last decade. The previous literature has taken the following approach: equation (3) is estimated empirically using the following type of single-equation model:

$$SWB_i = \alpha + \beta_1 Q_i + \beta_2 \ln(M_i) + \beta_3 X_i + \varepsilon_i \qquad (6)$$

where income is in logarithmic format. Life satisfaction has been the predominant measure of SWB used in these models. It takes responses from a question of the type: "*How disatisfied or satisfied are you with your life overall?"*, measured on a scale of 1 to 7 or 1 to 10 etc. Ferrer-i-Carbonell and Frijters (2004) have shown that it makes little difference whether we assume cardinality or ordinality in the life satisfaction variable and hence (7) is usually run assuming cardinality using ordinary least squares (OLS). In this paper for consistency I also focus on life satisfaction[2], but other measures of wellbeing can easily be used in the general framework presented here. Partial derivatives from the single equation model in (7) are used to estimate the value (here CS) of Q as:

$$CS = M^0 - e^{\left[\ln(M^0) - \frac{\beta_1 (Q^1 - Q^0)}{\beta_2}\right]} \qquad (7)$$

This approach, however, leads to biased estimates of CS and ES for Q. There are three main technical problems that I shall focus on here, some of which have been discussed in the literature elsewhere (eg, Welsch and Kuhling, 2009; Fujiwara and Campbell, 2011).

(i) Parametric restrictions

If we adjust equation (5) to account for a logarithmic format for income, we see that equation (7) does not estimate the correct measure of welfare change (here CS):

$$CS = M^0 - e^{\left[\ln(M^0) - \frac{\frac{\mathrm{d}\,SWB}{\mathrm{d}\,Q}(Q^1 - Q^0)}{\frac{\mathrm{d}\,SWB}{\mathrm{d}\,M}}\right]} \neq M^0 - e^{\left[\ln(M^0) - \frac{\beta_1 (Q^1 - Q^0)}{\beta_2}\right]} \qquad (8)$$

[2] The WV approach has also been called the life satisfaction approach in the literature.

Since $\frac{\mathrm{d}\, SWB}{\mathrm{d}\, Q} \neq \beta_1$ and $\frac{\mathrm{d}\, SWB}{\mathrm{d}\, M} \neq \beta_2$ due to the parametric restrictions in the single-equation framework (7). We cannot estimate the TEV of Q with (7). We can also stipulate that is likely that $\frac{\mathrm{d}\, SWB}{\mathrm{d}\, M} > \beta_2$, forcing up monetary equivalent values in (7), which is a common finding and criticism in the WV literature (B. S. Frey, et al., 2009) (see Clark & Oswald, 2002 for examples of high value estimates; Nattavudh Powdthavee, 2008). WV values have often been found to be magnitudes higher than values derived from RP and SP methods for environmental goods (Levinson,(2012); Luechinger (2009)). Furthermore, the relationships between the explanatory variables in (6) result in multicollinearity leading to inflated standard errors invalidating statistical inference. CS and ES should not be estimated using single-equation models.

(ii) Bias

To estimate welfare changes in equation (5) the total derivatives must have a causal attribution. In the wellbeing literature it is well-known that bias can arise from endogeneity, simultaneity and measurement error (Pischke, 2010). OLS is the predominant estimator used in WV, but it is likely to produce biased causal estimates. Some studies have instead used fixed effects models or instrumental variables (IV), but these approaches are still problematic. The fixed effects approach cannot control for time-varying unobservable factors and there is still the possibility of simultaneity bias and measurement error. In fact, fixed effects can exacerbate problems by increasing the ratio of measurement error to actual variation in variables that are measured with error (Deaton, 1993). As for IV techniques, a number of papers instrument for income and some for both income and the non-market good in two stage least squares (2SLS) (eg, Luechinger (2009) for air quality). But this does not provide a solution. First, the theoretical arguments behind income instruments in these papers tend to be weak. Commonly used instruments in WV include spouse's income, spouse's employment status and house ownership, predicted industry wage levels and social class (Ferreira & Moro, 2009; Luechinger, 2009; Luttmer, 2005; Pischke, 2010), which are unlikely to be independent of the potential treatment (here income) and life satisfaction: none are true exogenous shocks to income. Other studies in the wider wellbeing literature have used as instruments sight of payslips (N. Powdthavee, 2010) and father's years of education (Knight, Song, & Gunatilaka, 2009), again with concerns about adherence to exogeneity and exclusion restriction assumptions. Lottery wins have been used as IVs for income, but lottery wins have not been employed to estimate monetary values and as I shall argue below the ignorability assumptions have not been fully met in the lottery wins literature to date.

Second, using 2SLS in a single-equation framework (even with perfect instruments) cannot provide the correct solution: when more than one variable is instrumented in the same model (as in Luechinger (2009)) it is nearly always impossible to derive the total derivatives that we need to estimate ES and CS. To explain this, assume an optimal situation where robust random IVs exist for M and Q. If M and Q are correlated, then one of them has to be measured before the other in order to avoid the problem of indirect effects: we can only include M_t and Q_{t-1} (both instrumented) or vice versa in 2SLS. This means we cannot estimate a total derivative for the variable that is set at time $t-1$. This problem is further exacerbated when other controls are required in 2SLS for identification.

(iii) Undefined sample populations

Finally, there is the question of to whom the estimates apply and the issue of sample matching. A large majority of papers focus on a binary Q, for example, being employed, being healthy, living in a safe or polluted area etc, and I shall focus the discussion here on binary variables for Q. The issue of sample matching becomes problematic when we acknowledge heterogenous treatment effects. When using 2SLS causal estimates for Q and M may be coming from two different unobservable complier sub-populations, making sample matching impossible - further reason to avoid using 2SLS in WV. On the other hand, if OLS is used it provides poorly-defined estimators for M and Q, that lie somewhere between the average treatment effect for the treated (ATT) and the average treatment effect for the non-treated (ATNT) (Humphreys, 2009), which are different population groups. The samples used in the numerator and denominator in (5) should be the same (or come form the same population) and $\frac{\mathrm{d}\,SWB}{\mathrm{d}\,Q}$ should have a clear treatment effect interpretation so that we can make meaningful policy conclusions. For example, if $\frac{\mathrm{d}\,SWB}{\mathrm{d}\,Q}$ were estimated as the ATT, the monetary equivalent value would represent the *retrospective* value of Q (the policy) for those that were treated. The ATNT would tell us something about how valuable it would be if the policy were rolled out to those who were not initially treated (ie, the *prospective* value of the policy) and the ATE would give us a broad estimate of value for anyone picked from the general population.

4. New Approach to Wellbeing Valuation

In light of the above issues, the wellbeing model is clearly better explained and understood as a set of simultaneous equations in which SWB and the explanatory variables may be jointly determined and may interact with each other. The general approaches to estimating simultaneous equation models (SEM) are to use IV techniques or full-model maximum likelihood estimation (MLE) (Kline, 2005). Estimation through MLE requires a-priori knowledge of the relationships between all variables and the nature of the error terms and of course without exogenous variation in the explanatory variables we are unable to attribute causality – we still rely on a selection on observables story for identification. For IV estimation we have already discussed the associated problems in these circumstances.

The model developed here will be as flexible (and realistic) as possible - allowing for selection on unobservables and on unobservable gains and to provide estimates of welfare change that are relevant for policy. The main criteria will be for an approach that: (a) derives causal estimates for the impact of income and the good Q; (b) is non-parametric (or minimally parametric) so that indirect effects of Q and M can be acknowledged in order to derive total impacts on SWB and the TEV; and (c) derives well-defined causal estimates for a matched sample group.

Given the SEM framework, the solution I propose is to non-parametrically estimate the full wellbeing model in two separate stages; one stage for the income variable and the other for the Q variable of interest. In each stage exogenous changes in income and the non-market good should be employed, which means that we can estimate causal total derivatives for Q and M with well-defined treatment effects for Q. The models in these two stages should be estimated for the same sample population and from this the MRS between Q and M can be derived in the final stage of the process. This is what I shall call the **Three-Stage Wellbeing Valuation Approach (3S-WV)**.

4.1. Three-Stage Wellbeing Valuation

The basis of the 3S-WV approach is to estimate the following three equations:

STAGE 1. Income Model: $SWB_i = f(\ln(M_i))$ (9)

STAGE 2. Non-Market Good Model: $SWB_i = g(Q_i)$; (10)

STAGE 3. Monetary Equivalent Value: Calculate $MRS_{Q,M}$ using f'_M and g'_Q

where, (i) g'_Q has a well-defined treatment effect; (ii) g'_Q and f'_M are causal total derivatives ($g'_Q = \frac{\mathrm{d}\, SWB}{\mathrm{d}\, Q}$ and $f'_M = \frac{\mathrm{d}\, SWB}{\mathrm{d}\, M}$); and (iii) i is drawn from the same sub-population, hence 3S-WV will provide measures of CS and ES that are consistent with welfare economic theory as set out in (5). Equations (9) and (10) in effect internalise the system of simultaneous equations that make up the wellbeing model. The key point to note about 3S-WV is that it accommodates a variety of statistical methods - any mix of experimental and non-experimental techniques can be used to estimate the three stages, provided that the three modelling criteria are adhered to. Ideally (9) and (10) would be estimated in studies where treatment assignment has been randomised, but it would be possible to use other methods that are capable of deriving robust causal estimates under the right conditions, such as instrumental variables, difference-in-difference methods and regression discontinuity design. Indeed if a selection on observables assumption is appropriate, we could employ a matching estimator or OLS controlling only for pre-treatment covariates.

Table 2 provides the framework for estimating ES and CS in 3S-WV, where log of income is used in (9) to reflect diminishing marginal utility of income (for continuous Q variables it would also be possible to use formats to reflect non-linear marginal impacts on SWB).

Table 2. CS and ES in wellbeing valuation

	Compensating Surplus (CS)	**Equivalent Surplus (ES)**
Welfare gain	$CS = M^0 - e^{\left[\ln(M^0) - \frac{g'_Q}{f'_M}\right]}$	$ES = e^{\left[\frac{g'_Q}{f'_M} + \ln(M^0)\right]} - M^0$
Welfare loss	$CS = e^{\left[\frac{-g'_Q}{f'_M} + \ln(M^0)\right]} - M^0$	$ES = M^0 - e^{\left[\ln(M^0) + \frac{g'_Q}{f'_M}\right]}$

It is important to note that under this framework CS for welfare gains and ES for welfare losses are constrained at the level of an individual's income, whereas ES for welfare gains and CS for welfare losses have their limits at infinity as we would expect (Johansson, 1987). To see this, for example, take ES for a welfare loss. Here g'_Q is negative and for Q with very large negative impacts, such that $g'_Q \to -\infty$:

$$ES = M^0 - e^{\left[\ln(M^0) + \frac{g'_Q}{f'_M}\right]} = M^0 - e^{-\infty} = M^0 \quad (11)$$

For a given Q differences between ES and CS will emerge in this framework due to the curvature of the income function. For welfare gains, ES > CS. For welfare losses, CS > ES. The phenomenon of loss aversion that has been suggested to lead to the WTP-WTA disparity for a given good would come through in this framework if a given non-market good had a bigger absolute impact on SWB when it was taken away than when it was given to the individual.

4.2. Estimation in Three-Stage Wellbeing Valuation

We have noted that the 3S-WV model can be estimated with experimental and observational data. The 'gold standard' here would be to estimate g'_Q and f'_M from two separate studies where treatment (Q and M) are randomised. Assuming that the standard assumptions are met randomised trials (RCTs)[3] provide unbiased causal estimates with well-defined treatment effects – the ATE and ATT. Further, the non-parametric difference in means estimate from an RCT is the total derivative. We note that if (9) and (10) are estimated from the same sample, rather than from two non-overlapping random samples of the same population, it is likely that SWB outcomes will not be independent across i and hence bootstrap standard errors should be used for inference.

The main problem for this 'gold standard' approach is that at a practical level, in policymaking random assignment may not always be possible and it is unlikely that we will be able to randomise income in large samples due to financial, political and ethical constraints. This is problematic because of the central role that income plays in the WV approach. It turns out, therefore, that the income model (equation (9)) will need to be estimated using non-experimental data and then matched to estimates of g'_Q from equation

[3] I use the term 'RCT' to include any study where treatment has been randomised, such as field experiments.

(10). In this paper I use lottery wins as an instrumental variable for income and derive causal estimates of the total derivative ($\frac{\mathrm{d}\, SWB}{\mathrm{d}\, M}$) using minimal parametric restrictions. I employ a *control function* approach, instead of traditional 2SLS, in order to derive a treatment effect of income for a clearly defined sample population, rather than the unobservable complier subset (the approach set out here is to use an IV for income, but any other method that is able to derive causal estimates for income in (9) can be used instead). It is possible, then, to match this estimate of f'_M with an estimate of g'_Q that has a robust causal interpretation.

In this paper, as an example, I will derive the *compensating* and *equivalent surplus* for unemployment over and above the impact of loss of wage income using the British Household Panel Survey (BHPS). In other words this will be the monetary equivalent value of the non-financial costs associated with unemployment. The income model is estimated using the CF approach and a natural experiment is used in the non-market good (unemployment) model (10). I derive the average partial effect (APE) for income, which will be relevant to the general population rather than an unidentified complier sub-group, which means that we can ensure sample matching. Because of its generality, the APE income estimate can actually be used as an 'off-the-shelf' estimate of the income model (9) in other WV studies; it would be possible to use the causal estimate of income derived here for all subsequent WV studies that use the BHPS or another dataset that is representative of the UK. The g'_Q parameter will also be derived as the average effect for the same sample – it will be the ATE for unemployment (this is a non-market 'bad', but I shall call it a treatment in order to refer back to the treatment effects literature). The monetary equivalent value derived here has a clear interpretation; it is the cost of unemployment for a randomly selected person from the UK population.

4.2.1. STAGE 1: The income model

The income variable is likely to suffer from simultaneity and endogeneity bias and measurement error. The clearest exogenous changes in income we will be able to find in national surveys are most likely to come from lottery wins and a small literature uses lottery wins to identify causal effects of income on wellbeing and health. Apouey and Clark (2009) and Gardner and Oswald (2007) use lottery wins themselves from the BHPS as an explanatory variable and they find positive impacts on health and wellbeing. Lindahl (2005 uses data on Swedish lottery winners in 2SLS and finds positive impacts on health. The main caveat to these studies is that data in the BHPS and from Sweden only provides information on the size of annual lottery wins. We do not know how often people play and so annual lottery wins are not strictly exogenous: people who play more are more likely to win more money and this is problematic as those who play more are also likely to have different levels of potential income to start off with. Lindahl (2005) and Apouey and Clark (2009) show that annual lottery wins in both datasets are correlated with a host of socioeconomic variables and this is why all of the papers hold these variables constant in an attempt to ensure exogeneity in the lottery prize variable. However, the fact that these variables are determinants of win size means that there are also likely to be a host of other *unobservable* variables that are correlated with win size and income and which we cannot control for. Hence, only controlling for some of the observable characteristics that determine winnings per year is unlikely to produce unbiased casual estimates for income. A second problem is that the localised complier-relevant estimates from 2SLS are too narrow for use in WV and we do not know the populations to whom the estimates can be generalised.

A different approach is taken here with the lottery wins data from the BHPS. Firstly, I hypothesise that the amount of previous lottery wins will capture lottery playing preferences and hence current playing frequency much more accurately than observable socioeconomic factors - on the assumption that people who play a lot in the past will always tend to play a lot, unless they win very large amounts, but these people are excluded from the analysis. I find that controlling for previous wins leaves all other observable background variables statistically insignificant in determining annual lottery win size (see Table 4) - evidence that controlling for previous wins will ensure exogeneity in the lottery wins instrument, arguably something that was not achieved in the previous literature.

The second difference is that I use a *control function* (CF) approach instead of 2SLS. As discussed, 2SLS derives local average effects for an undefined complier sub-group, which makes it impossible to sample match in WV. Under some additional assumptions (to standard 2SLS), the CF approach will allow us to derive estimates of the sample average partial effect (APE) for income, which is a clear treatment effect for a well-defined sample group. The CF approach is preferred here to other methods in the literature that attempt to extrapolate localised IV effects (LATE) to population average effects (see for example, Aronow and Sovey (2010), Follmann (2000) and Angrist and Fernandes-Val (2010)). These methods are problematic because they assume that sub-group differences in LATEs can be explained solely by observable characteristics and because extrapolation requires knowledge of non-compliers' (always-takers and never-takers) treatment effects, for which no counterfactual or causal effect exists. The CF approach does not rely on these assumptions. The methodology set out here will allow us to get unbiased causal estimates for income for a well-defined general population group.

Data and methodology

Both the income and unemployment model presented here use data from the BHPS, which is a nationally representative sample of British households, containing over 10,000 adults, conducted every year since 1991. Life satisfaction (measured on a scale of 1 – 7) was added in 1997 and so we analyse the period 1997- 2009, excluding 2001 which did not include life satisfaction questions. The BHPS asks respondents whether they have won money on lotteries or football pools and how much they have won in total during the year. In the UK there are a large number of lottery players (Wardle, 2010) and these swamp the football pool players in the BHPS dataset (Gardner & Oswald, 2007). I will therefore refer to this group simply as lottery winners as Gardner and Oswald (2007) do. Table 3 shows the descriptions for all variables used in this paper. Since I run a number of models I do not provide descriptive statistics (mean and standard deviation) for the variables as they will differ for each model (due to different samples), but they can be obtained from the author if required.

Table 3. Variable descriptions

Variables	Descriptions
Life satisfaction	Life satisfaction score, coded on a seven-point scale so that 1 = very dissatisfied, 7 = completely satisfied
Job satisfaction	Job satisfaction score, coded on a seven-point scale so that 1 = very dissatisfied, 7 = completely satisfied
Household income	Annual equivalised gross household income
Household size	Number of people living in the home
House ownership	= 1 if respondents owns their home
Unemployed	= 1 if not employed or self-employed
Spouse employed	= 1 if spouse is employed or self-employed
Redundant unemployed	= 1 if respondent was made redundant (and is still unemployed)
Retired	= 1 if retired
Job hours	Hours worked per week
Male	= 1 if male
Age	Age of respondent
Low education	=1 if left education after minimum compulsory
Poor health	= 1 if respondent assesses own health as 'poor' or ' very poor'
Carer	= 1 if respondent provides care of others
Previous lottery wins	Sum of previous lottery wins (£)
Lottery win	= 1 if respondent won between £100 - £50,000 in lotteries over the year
No. of children	Number of children under age 16 in the household
Married	= 1 if married)
Divorced	= 1 if divorced
Widowed	= 1if widowed
Separated	= 1 if separated
Never married	= 1 if never married
Winter interview	= 1 if survey was taken in winter
Living in safe area	= 1 if respondent does not live in an area where they perceive vandalism and crime to be a problem.
Debt burden	= 1 if repayment of debt and associated interest is a 'heavy burden' or 'somewhat of a burden'

I use the CF approach to run a correlated random coefficient (CRC) model using lottery wins as an IV (Z) for household income and controlling for previous lottery wins. For previous wins, I sum annual lottery wins over all years in which the respondent was present in the data up to $t-1$. Following Heckman and Vytlacil (ref 1998) the model is set up as follows (dropping the time and individual subscripts for simplicity):

$$LS = \pi + \beta_1 \ln(M) + \beta_2 X + \varepsilon \tag{12}$$

$$\beta_1 = \alpha_1 + \vartheta_1 \tag{13}$$

$$\ln(M) = \pi + \gamma Z + \vartheta_2 \tag{14}$$

so that,

$$LS = \pi + \alpha_1 \ln(M) + \beta_2 X + \vartheta_1 \cdot \ln(M) + \varepsilon \tag{15}$$

where ϑ_1 is unobserved heterogeneity that interacts with income and $E(\beta_1)$ is the sample APE for income. Since M is endogenous in (12), ε and ϑ_2 are correlated, and under the assumption of heterogenous treatment effects ϑ_1 and ϑ_2 are also correlated. Therefore, ϑ_1 and ε in (15) are estimable from the error term in (14): $E(\vartheta_1|X,M) = \theta_1\vartheta_2,\ E(\varepsilon|X,M) = \rho_1\vartheta_2$. Equation (15) then becomes:

$$LS = \pi + \alpha_1 \ln(M) + \beta_2 X + \theta_1\hat{\vartheta}_2 \cdot \ln(M) + \rho_1\hat{\vartheta}_2 \tag{16}$$

where $\hat{\vartheta}_2$ is the predicted error terms from (14). The assumptions underlying the CRC model are somewhat more restrictive than those for 2SLS. In addition to the standard assumptions for valid instruments, we assume here that (14) is linear and that $E(\varepsilon|\vartheta_2)$ and $E(\vartheta_1|\vartheta_2)$ (respectively unobserved self-selection and unobserved selection on gains) are linear functions. Also, we note that the composite error term in (15) (ie, $\vartheta_1 \cdot \ln(M) + \varepsilon$) has a non-zero heterosckedastic mean and so robust standard errors are used. Under these assumptions α_1 in (16) represents the causal effect of log of household income on life satisfaction for the average person in the sample. It is noted that we do not require the monotonicity assumption in this set-up because we can assume that we have one-sided non-compliance to the instrument – in other words, it is reasonable to assume that the subject pool comprises of compliers and always-takers. Never-takers would be people that do not cash in on winning lottery tickets, which seems unlikely. Table 4 shows that controlling for previous lottery wins ensures exogeneity in Z.

Table 4. Determinants of annual lottery wins size

Independent variables	Coefficient	S.E.
low education	136.903	117.398
age	-2.066	-3.457
male	129.526	112.586
poor Health	-154.732	-200.634
unemployed	-98.941	-446.597
no. of children	81.733	70.75
lagged income	-0.001	-0.002
previous lottery wins	0.07***	0.014
constant	249.086	228.99
Observations	5,269	

Therefore we use a conditional independence assumption :

$$(Y_0, Y_1, D_0, D_1) \perp Z \mid \text{previous wins} \tag{17}$$

where in this case Y is life satisfaction, the “treatment” (D) is an increase in income and Z is lottery wins. This implies that (conditional on previous win amounts) lottery wins cannot be correlated with other determinants of household income (exogeneity) and that lottery wins can only affect life satisfaction through the impact on income (exclusion restriction). Note here that previous wins is a pre-treatment variable so income can still have indirect effects on wellbeing and hence $\alpha_1 = \frac{\mathrm{d}\,SWB}{\mathrm{d}\,M}$. It should be noted that the estimation procedure set out here still has some parametric restrictions in that the impact of income on wellbeing is assumed to take a logarithmic format, but there is evidence to support this (Layard, Nicholl, & Mayarz, 2008).

It could be argued that the exclusion restriction could fail here as lottery winners may also be happier because of euphoria experienced at winning the lottery. Therefore, the present paper compares lottery winners of different amounts as in Gardner and Oswald (2007) and Imbens et al. (2001). $Z = 0$ for people with (small) annual wins of under £100 and $Z = 1$ for people with medium sized annual wins of £100 to £50,000. Wins are restricted to a maximum of £50,000 since sample sizes get very low after this point, which makes extrapolation shaky.

Here both groups are winners and will feel some happiness due to having won. Is there still a problem that larger winners (the $Z = 1$ group) may feel more euphoria than smaller winners (the $Z = 0$ group)? This is will be undoubtedly true, but it suggests that the level of euphoria experienced at winning the lottery is correlated with win size, which suggests that it is the money prize that causes happiness; precisely the effect we are interested in for the instrument. Second, the euphoria felt from the act of winning itself may only be temporary anyway and not picked up in the life satisfaction responses at the time of the survey.

Comparing the sample of small to medium-sized lottery winners has implications for our interpretation of the APE. The CF will derive the causal effect of income for the average lottery player. This means that for valuation we would have to either estimate g'_Q for the average lottery player in the UK or find a way of converting the APE for lottery players to the general population APE. The latter is preferable and since the evidence suggests that a large proportion of the UK population (over 70%) play lotteries we will assume here that the sample APE from the CF is equivalent to the population APE and we can match this with the population average estimate of g'_Q.

Results

Table 5 presents the results of the CF model for income. The first stage is equation (14). I find that winning the lottery has a highly significant positive effect on household income after controlling for previous win amounts. In the control function the sample APE of log of household income on life satisfaction is 1.1, which is also highly significant. This represents the causal effect of income on life satisfaction for any lottery player chosen at random, which we can assume to represent the average effect for the UK population. No post-treatment variables are included in the model and hence this is the *full* causal effect (the total derivative) of household income on life satisfaction:

$$\frac{\mathrm{d}\, SWB}{\mathrm{d}\, M} = 1.1 \tag{18}$$

Table 5. The causal effect of income on life satisfaction

First stage regression (equation (14))

Dependent variable: log(household income)

Independent variables	Coefficient	S.E.
lottery win	0.102***	0.015
previous lottery wins	6.82e-06***	0.000
constant	9.999***	0.007
Observations	10,461	

Control Function (equation (16))

Dependent variable: life satisfaction

Independent variables	Coefficient	S.E.
log (household income)	1.103***	0.252
previous lottery wins	-0.00001***	-0.000
$\hat{\vartheta}_2$	-1.108***	-0.260
$\hat{\vartheta}_2 \cdot \ln(M)$	0.011*	0.006
constant	-5.777**	-2.530
Observations	10,328	

We note that $\hat{\vartheta}_2$ is significant which is proof that the income variable is endogenous in the life satisfaction equation and is likely that standard OLS would generate biased estimates of the causal effect of income. The coefficient is negative implying that in cases where income is not exogenously determined we will see downward bias in the income coefficient. As we shall see below, OLS estimates of the impact of income are magnitudes lower than the casual effect estimated in Table 5. The interactive term ($\hat{\vartheta}_2 \cdot \ln(M)$) is significant at the 10% level, showing some evidence for heterogenous impacts of income.

4.2.2. STAGE 2: The non-market good model (unemployment)

I use involuntary redundancy to estimate the causal effect of unemployment on life satisfaction. It turns out that the involuntary redundancy variable in the BHPS can be seen as naturally occurring or exogenous to life satisfaction. Table 6 shows evidence that redundancy decisions seem to be 'as good as randomly assigned' in the BHPS because a range of pre-redundancy variables are balanced between the redundant and employed groups (see columns

(i) – (iii)). Columns (iv) – (vi) show that this is not the case when comparing the sample of general unemployed with the employed. Although there is likely to be some 'selection' into redundancy by those who are less productive, less motivated, in poor health and with caring duties etc, the manner in which the job termination question in the BHPS is asked seems to solve this issue for us because in the question itself people can state that they terminated their last job because of health reasons, caring duties or because they were sacked and so on.

Table 6: Balance of covariates across unemployed and employed

Variable (measured pre-unemployment)	(i) Redundant unemployed	(ii) Employed	(iii) Difference	(iv) General unemployed	(v) Employed	(vi) Difference
Life satisfaction	5.05	5.1	0.05 (p=0.70)	4.8	5.13	0.33*** (p=0.0)
Job satisfaction	3.97	3.78	0.19 (p=0.41)	2.91	3.88	0.97*** (p=0.0)
Labour income	£11,400	£11,008	£392 (p=0.82)	£6,760	£11,494	£4734*** (p=0.0)
Job hours	34.35	34.19	0.16 (p=0.9)	33.29	34.26	0.98 (p=0.11)
Health (annual no. of visits to GP)	2.19	2.29	0.19 (p=0.34)	2.34	2.28	0.06 (p=0.12)
Carer	4.42%	3.24%	1.2 (p=0.48)	4.09%	3.17%	0.9 (p=0.2)
Married	45.70%	43%	2.7 (p=0.21)	22.20%	45.50%	23*** (p=0.0)
House owned	66.40%	68.40%	20 (p=0.64)	51.70%	70.30%	18.6*** (p=0.0)
Household size	3.1	3.1	0.09 (p=0.13)	3.28	3.08	0.20*** (p=0.0)
Debt burden	20.40%	17.40%	3 (p=0.40)	17.80%	17.40%	0.4 (p=0.77)

Consequently, and as we would expect, the unemployment variable (redundant unemployed) is highly robust to the inclusion of other important covariates in regression analysis in Table 7: the coefficient staying constant at -0.44.

Table 7: The causal effect of unemployment on life satisfaction

Independent variables	(1)		(2)	
	Coefficient	S.E.	Coefficient	S.E.
Redundant unemployed	-0.441***	-0.065	-0.436***	-0.062
Log (household income)	0.164***	0.012	0.092***	0.013
Retired			0.209***	0.048
Poor health			-0.150***	-0.008
Age			-0.067***	-0.005
Age^2			0.001***	0.000
Married			0.086***	0.023
Divorced			-0.243***	-0.050
Widowed			-0.283***	-0.085
Separated			-0.464***	-0.070
Never married			-0.242***	-0.033
Carer			-0.113**	-0.046
Low education			0.023	0.016
Wales			-0.008	-0.024
Scotland			-0.017	-0.021
N. Ireland			0.178***	0.031
Live in safe area			0.153***	0.021
Debt burden			-0.315***	-0.022
Winter interview			-0.004	-0.018
House owned			0.099***	0.019
Spouse employed			0.124***	0.026
Number of children			-0.007	-0.010
Year			-0.004*	-0.002
Constant	3.549***	(0.120)	5.735***	0.146
Observations	24,411		24,395	
R-Squared	0.011		0.078	

In these models, income is held constant so that we can measure the non-financial impacts of unemployment on life satisfaction. Since causal identification does not rely on conditioning on other variables we can drop all other covariates here and use the model in column (1) of Table 7 so that we avoid the indirect effects problem. Furthermore, we are able to derive a well-defined treatment effect. We interpret the result from this model as showing that being unemployed *causally* reduces life satisfaction (over and above the impact on wage income) by 0.44 points for the average person in the sample, which is representative of the UK (it is the sample average effect of unemployment). This estimate includes all channels through which unemployment impacts on life satisfaction, such as through worse health:

$$\frac{\mathrm{d}\,SWB}{\mathrm{d}\,Q} = -\,0.44 \qquad (19)$$

This is the impact for the first year in unemployment and it includes the impact of entry into unemployment and the state of being unemployed for that first year.

4.2.3. STAGE 3: The monetary equivalent cost of unemployment

Using equations from Table 2 and results from Tables 5 and 7, we derive the CS and ES of unemployment (we use a sample median income of £23,000):

Compensating surplus for unemployment

$$CS = e^{\left[\frac{-g'_Q}{f'_M} + \ln(M^0)\right]} - M^0 = e^{\left[\frac{0.44}{1.1} + \ln(23{,}000)\right]} - 23{,}000 = \text{£}\boldsymbol{11{,}312\ per\ year}$$

This is the amount of extra annual household income that would be required in order to keep a randomly chosen employed person just as satisfied with life if he were made unemployed (after controlling for loss of wage income).

Equivalent surplus for unemployment:

$$ES = M^0 - e^{\left[\ln(M^0) + \frac{g'_Q}{f'_M}\right]} = 23{,}000 - e^{\left[\ln(23{,}000) - \frac{0.44}{1.1}\right]} = \text{£}\boldsymbol{7{,}583\ per\ year}$$

This is the amount of money one would need to take away from a randomly selected individual in employment to reduce his life satisfaction to the levels he would experience if he were unemployed (after controlling for loss of wage income).

These are unbiased estimates of CS and ES for unemployment, with a clear interpretation for policy purposes. As expected CS is larger than ES and arguably CS is the preferred measure as it is the commonly used measure in non-market valuation. To show the level of bias one would confront using standard WV methods in Table 8 I show coefficients for log of household income (un-instrumented) and for unemployment status (where the unemployed are the whole sample of unemployed people) from a pooled OLS model. I include all variables from column 2 of Table 7 except for spouse employment status since it is not usually included in WV studies and number of children as it was highly insignificant. This is a typical type of model used in the WV literature and as discussed it will usually lead to biased estimates.

Table 8: Pooled-OLS life satisfaction model

Independent variables	Coefficient	S.E.
Unemployed	-0.51***	-0.031
Log (household income)	0.08***	0.012
Observations	24,395	
R-squared	0.088	

Compared to our causal estimate of unemployment, we see that the standard OLS model produces an over-bias in the coefficient on unemployment. This seems intuitively right as we would expect certain individuals to be more likely to become unemployed and be less satisfied with life anyway. The bias in the income coefficient is much more severe. The causal estimate derived from lottery winners is more than ten times larger than the OLS estimate. This direction of change is expected given that instrumenting for income generally tends to result in an increase in coefficient size (Pischke, 2010). The income coefficient may have increased using the lottery instrument because (a) people who would be happy anyway tend to earn less money, (b) income is measured with error and (c) many of the indirect effects of income are controlled for in OLS.

For the pooled-OLS model CS for unemployment is about £13m per year and ES is £22,959 per year. These values are clearly implausibly too high due to the severe biases, reflecting many of the findings from the previous WV literature. We also note that the values derived from the pooled-OLS model do not have properly defined treatment effects and hence we cannot attribute them to a relevant population group. In sum, this shows that the traditional single-equation methods should not be used to value non-market goods in wellbeing valuation.

5. Discussion

We have used the 3S-WV approach to derive robust values associated with employment. This was based on models that use exogenous changes in income and in employment status. The estimate for the causal effect of income (f'_M) is generic enough to be used elsewhere. The Appendix provides a quick-reference table to show the predicted values for different hypothetical impacts sizes of Q on life satisfaction using the estimate of f'_M from this paper.

It is possible to run 3S-WV with models that do not utilise exogenous changes in the variables of interest, but it should be stressed that outside of the case of perfectly observable eligibility as in the RDD case, standard selection on observables methods - such as matching and OLS - should be seen as second-best options for 3S-WV, only to be considered when (i) random assignment of the non-market good (Q) is not possible, (ii) study designs that allow for selection on unobservables are not available and (iii) the selection on observables assumption is realistic.

In this paper we have not covered some of the other technical issues that have been highlighted in the literature, including the implications of relative income effects and adaptation for the WV approach. It was out of the scope of this paper to include these issues since arguably they are less severe and less complicated and their implications relate to interpretation of the results rather than to any bias. However, these are issues we should look at going forward.

6. Conclusion

Non-market good valuation is central to CBA and policy evaluation. Wellbeing valuation is a recently developed approach and the problem is that the current methodology produces significantly biased estimates of compensating and equivalent surplus for non-market goods, which are not useful for policy. The 3S-WV approach solves for the main technical problems and provides estimates of compensating and equivalent surplus that are consistent with economic theory and that have well-defined interpretations for policy-making. 3S-WV can be used with both experimental and observational data or a combination of both and in this paper we use 3S-WV to derive unbiased estimates of compensating and equivalent surplus for unemployment using observational data. The example used here shows that 3S-WV derives much more plausible value estimates for non-market goods than previous methods. These valuations are alternatives to values derived using preference-based approaches and are now robust for use in CBA and policy-making.

Appendix

Table A1 offers a quick-reference chart of values (CS) for hypothetical impacts sizes based on the causal effect of log of income of 1.1 and an average income of £23,000. This gives an idea of the values associated with different coefficient sizes for non-market goods or 'bads'. The values are based on life satisfaction models where life satisfaction is measured on a scale of 1-7.

Table A1. Monetary equivalent values for hypothetical wellbeing impacts

Hypothetical impact size for ***Q***	CS for welfare gain	Hypothetical impact size for ***Q***	CS for welfare loss
0.0001	£2	-0.0001	£2
0.0005	£10	-0.0005	£10
0.001	£21	-0.001	£21
0.005	£104	-0.005	£105
0.01	£208	-0.01	£210
0.05	£1,022	-0.05	£1,070
0.1	£1,999	-0.1	£2,189
0.25	£4,676	-0.25	£5,869
0.5	£8,401	-0.5	£13,235
0.75	£11,369	-0.75	£22,482
1	£13,733	-1	£34,087
1.5	£17,118	-1.5	£66,939
2	£19,267	-2	£118,695

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